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Carbon Curse in Developed Countries

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Abstract

Among the ten countries with the highest carbon intensity, six are natural resource-rich countries. This suggests the existence of a carbon curse: resource-rich countries would tend to follow more carbon-intensive development paths than resource-poor countries. We investigate this assumption empirically using a panel data method covering 29 countries (OECD and BRIC) and seven sectors over the 1995–2009 period. First, at the macroeconomic level, we find that the relationship between national CO_2 emissions per unit of GDP and abundance in natural resources is U-shaped. The carbon curse appears only after the turning point. Second, we measure the impact of resource abundance on sectoral emissions for two groups of countries based on their resource endowments. We show that a country rich in natural resources pollutes relatively more in resource-related sectors as well as all other sectors. Our results suggest that the debate on climate change mitigation should rather focus on a comparison of resource-rich countries versus resource-poor countries than the developed-country versus developing-country debate.

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

JEL codes: Q32 - Q53.

1 Introduction

In early 2019, China announced the discovery of oil reserves that could trigger a surge in shale drilling. This discovery confirms estimates by the U.S. Energy Information Administration that China has abundant shale gas and shale oil potential. What could be the consequences of the increase in resource abundance on greenhouse gas emissions? In the specific case of China, more resources induce more growth and hence more energy consumption. However, oil may substitute coal, which could decrease CO_2 emissions. The

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effect of such discoveries in natural resources on CO_2 emissions may be crucial since world emissions are still increasing, despite international mitigation commitments like the *Paris Agreement* (2016). The continuous rise in emissions is due mainly to industrial production, transport and heating in addition to the energy mix. The more fossil fuels remain important in the energy mix, the higher the CO_2 emissions will be. Regulating these sources of emissions may harm growth, competitiveness, mobility, and individuals' purchasing power. These potential consequences explain the public opposition to environmental regulation and the reluctance of many countries to make strong commitments. In this paper, we argue that in addition to the usual drivers of CO_2 emissions, natural resource abundance plays a crucial role. Indeed, natural resources and the associated sectors, like extraction and energy production (refining), together with the use of fossil fuels cause pollution. Friedrichs and Inderwildi (2013) defined the link between fossil fuel resources and CO_2 emissions as the *carbon curse assumption*: countries rich in coal, oil, and gas emit more CO_2 to generate the same amount of economic output as countries lacking in fossil fuels. Thus, a fossil resource-rich country tends to be a *rich* country with significant CO_2 emissions. The relationships between resources and economic growth have already been widely discussed in the literature. Studies conclude that there are links between natural resources and economic growth (resource curse) and interactions between pollution levels and economic growth (the Environmental Kuznets Curve "EKC"). Our work is at the crossroads of these two fields since we investigate more generally the relationship between natural resources and CO_2 emissions to test an *extended* carbon curse assumption. According to Friedrichs and Inderwildi (2013), the carbon curse results from the relationship between CO_2 emissions and the abundance of fossil energy resources. We extend this analysis by including mineral resources in the definition of abundance. All the effects of resources are thus taken into account. Firstly, both types of resources have direct effects: the combustion of fossil fuels is highly emitting, while the extraction of minerals involves both surface and underground mining techniques (e.g. water pumping, hauling, ventilation, etc), which need huge quantity of energy (see Norgate and Haque, 2010). Secondly, in the spirit of the resource curse, resource endowment may induce a technological lag of resource rich countries, regardless of the type of resources, which may explain the energy-inefficiency of their production.[1]

We aim at assessing whether a country rich in natural resources is more polluting than another country and whether resource abundance affects all sectors of the economy. Our objective is to contribute to the debate on climate change mitigation by measuring the consequences of abundance in natural resources on emissions at different levels: national and sectoral. Our empirical analysis relies on extensive panel data covering 29 countries and seven sectors, over the 1995–2009 period. The combination of these data allows

[1] The results related to the Friedrichs-Inderwildi definition of the carbon curse are presented in Tables 6 and A.5.

for an original analysis that sheds light on mechanisms that have hitherto been ignored at the sectoral level.

This study is related to two strands of the literature mentioned above: the first strand investigates the link between economic growth and pollution emissions (EKC), and the second 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. Several 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 (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 the EKC hypothesis, economic growth could be the remedy to environmental problems in the long-term. Since the beginning of the 1990s, the EKC has become an independent and essentially empirical research domain, following the work of Grossman and Krueger (1995), Shafik and Bandyopadhyay (1992) Panayotou et al. (1993), Selden and Song (1994), and Galeotti (2007). However, the conclusions are ambiguous. On the one hand, some research has confirmed the existence of an EKC for different measurements of environmental degradation; see Panayotou et al. (1993) and Selden and Song (1994). On the other hand, several studies 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 the level of aggregation of the data (time series, cross-section, or panel) and the pollutant under consideration. Nevertheless, studies on CO_2 tend 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 body of 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 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 terms of trade that results from the real exchange rate appreciation following a resource boom. This shift in terms of trade has a negative impact on non-resource sectors. A second channel is the negative effect of natural resources on education. Following Gylfason (2001) and Sachs and Warner (1995), natural resource abundance 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. Lastly, the volatility in resource prices could increase macroeconomic instability, which in turn inhibits growth (Van der Ploeg and Poelhekke, 2009).

In the end, these two literature strands do not allow for a simple understanding of the links between natural resources abundance and CO_2 emissions, which are rarely tested directly. Wang et al. (2019) find evidence of a negative correlation between natural resource dependence (not abundance[2]), measured as the share of extractive sector activity in industrial production, and carbon emissions efficiency in Chinese provinces over the period 2003-2016. This work focuses on the carbon reduction potential of the Chinese economy, which is subject to some specific constraints (emerging country), whereas we are interested in the carbon intensity for a broader sample of countries. On the other hand, Balsalobre-Lorente et al. (2018) show the existence of an N-shaped EKC for five European countries (France, Germany, Italy, Spain and the United Kingdom), in which the abundance of natural resources is one of the factors in reducing CO_2 emissions for the period 1985-2016.

In our article, we deeply analyze the interactions between natural resources and pollution and investigate empirically the carbon curse assumption to check whether a higher abundance of natural resources implies higher carbon intensity. To the best of our knowledge, this study is thus the first to go beyond a simple descriptive statistical analysis by proposing econometric tests of the carbon curse assumption. The main intuitions for the mechanisms at stake for a carbon curse are as follows. First is a *composition effect* induced by the predominance of fossil fuel sectors which massively emit CO_2. Second are the *crowding out effects* in the energy generation sector, which forms a barrier to the development of renewable energy sources. Third are the *spillover effects* in other sectors of the economy, which are combined with less stringent policies. According to Friedrichs and Inderwildi (2013), very few resource-rich countries avoid the carbon curse, except for those suffering from the resource curse. However, the literature on EKC and the resource curse often points out the crucial role of economic development and the quality of institutions. By focusing on a group of developed countries, we highlight the importance of a novel argument based on resource abundance.

While Friedrichs and Inderwildi (2013)'s results are based on descriptive statistics with cross-sectional

[2]except in a robustness test where they use fossil energy endowment as an explanatory variable

data, we apply econometric methods to provide detailed evidence for the carbon curse assumption and explain its mechanisms. We consider both macroeconomic and sectoral data for a group of developed countries. Our database includes 29 developed countries, including the BRIC, and spans over 15 years (1995–2009); it reveals considerable heterogeneity between the countries. Our sectoral data consider seven sectors. This magnitude of data, both geographically and temporally, makes it possible to measure the complexity of the carbon curse hypothesis better.

We find that the interaction between CO_2 intensity of GDP and resource abundance is non-monotonous. More specifically, our results show a U-shaped relationship between CO_2 intensity and resource endowment at the country level: above a turning point, the more natural resource-rich a country is, the more it will emit CO_2 per unit of GDP. We also find that national CO_2 intensity is explained by the energy mix, environmental policy stringency, and technological level. Thus, to explain this U-shaped relationship at the country level, we rely on a sectoral analysis using sectoral CO_2 emissions intensity. The results show that abundance has a different impact on the sectoral CO_2 intensity across sectors with spillover effects among all sectors (even in the services sector). Interestingly, resource-rich and relatively resource-poor countries show opposite results.

The remainder of the paper is structured as follows. In section 2, we develop a simple accounting decomposition to explain the carbon curse assumption. Section 3 describes the data used. Section 4 presents the methodological approach and Section 5, the empirical findings. The interpretation of the results and robustness checks are presented in Section 6, and Section 7 concludes.

2 A simple decomposition

Drawing on the works of Grossman and Krueger (1995) and Copeland and Taylor (2004), we first propose a simple accounting framework. The objective is to break down changes in the CO_2 intensity into components that reflect changes in energy consumption, energy intensity, and industrial structure of the overall economy. This type of breakdown has been largely used in the EKC literature. We build on these previous works and propose a new decomposition for CO_2 emissions at the crossroads of the EKC and carbon curse literature.

We focus on the main factors that could explain the total changes in CO_2 intensity (CO_2/GDP). Total CO_2 emissions can be measured by the following decomposition:

$$CO_2 = \sum_i \sum_h \frac{\phi_{ih} E_{ih}}{E_i} \frac{E_i}{VA_i} \frac{VA_i}{GDP} GDP, \tag{1}$$

where E_{ih} is the consumption of energy of type h in sector i; ϕ_{ih} is the net CO_2 emissions intensity from energy h in sector i; E_i is the total energy consumption in sector i; VA_i refers to economic output in sector i (Value Added); GDP is the total economic output. ϕ_{ih} depends on the type of energy used (*i.e.* gas, coal, oil, biomass, renewables, and others) but also depends on the sector's decarbonation technology (CCS technology, for instance).

We consider two sources of energy: fossil energy (f) and renewables (r) with $\phi_{if} > \phi_{ir} \geqslant 0$. We also consider seven sectors ($i = 1, ...7$): mining, services, agriculture, transport, manufacturing, construction, and electricity, respectively.

Dividing both sides of Eq. (1) by GDP gives Eq. (2) which measures the overall CO_2 intensity $I_\varepsilon = CO_2/GDP$:[3]

$$I_\varepsilon = \sum_{i=1}^{7} \sum_{h=r,f} \phi_{ih}.U_{ih}.I_i.S_i, \tag{2}$$

where U_{ih} is the share of consumption of energy source h in sector i ($\frac{E_{ih}}{E_i}$), I_i is the energy intensity $\left(\frac{E_i}{VA_i}\right)$, and S_i is the share of sector i's output in the overall economy $\left(\frac{VA_i}{GDP}\right)$.

The net emission rate per unit of energy used, ϕ_{ih}, should depend on the level of technology, which itself is influenced by the stringency of the environmental regulation. As in the EKC literature, the net emission rate is supposed to be negatively related to the environmental regulation stringency. If the stringency is also negatively influenced by the resource abundance, there will be an impact on the net emission rate.

This simple accounting decomposition emphasizes the carbon curse mechanisms, where resource abundance explains the share of the mining sector in total GDP (S_1), which should influence the energy mix $\frac{E_f}{E}$ (where for $h = r, f$, $E_h = \sum_{i=1}^{7} E_{ih}$ and $E = \sum_{h=r,f} E_h$), the share U_{if} and the energy intensity I_i:

- a *composition effect*, induced by the share of the mining sector in the GDP (S_1), given that this sector is a massive CO_2 emitter;

- a *crowding out effect* in the energy generation process, forming a barrier to the development of renewable energy sources. This implies a high share of the consumption of fossil energy in all sectors (high $U_{if}, \forall i$) compared to renewable energies (low $U_{ir}, \forall i$);[4]

- *spillover effects* in other sectors of the economy (high $I_i, \forall i$) combined with less stringent policies (high $\phi_{ih}, \forall i, h$).

At the macroeconomic level, if we assume (for simplicity) that renewable energies are non-polluting

[3] At the sectoral level, the breakdown simply gives $\frac{CO2_i}{VA_i} = \sum_{h=r}^{f} \frac{\phi_{ih} E_{ih}}{E_i} \frac{E_i}{VA_i}$.

[4] Johnsson et al. (2019) show that fossil resource-rich countries have experienced a large increase in primary energy demand from fossil fuels, but only a moderate or no increase in primary energy from renewables.

($\phi_{ir} = 0$), we obtain:

$$\frac{CO_2}{GDP} = \phi_f \frac{E_f}{E} \frac{E}{GDP}, \tag{3}$$

which gives, in terms of growth rate (taking logs and differentiating):

$$\widehat{\frac{CO_2}{GDP}} = \widehat{\phi_f} + \widehat{\frac{E_f}{E}} + \widehat{\frac{E}{GDP}}.$$

Growth of emissions intensity could be explained by the technical progress in the fossil fuel sector $\widehat{\phi_f}$, the variation in the fossil component of the energy mix $\widehat{\frac{E_f}{E}}$, and in the energy intensity of GDP $\widehat{\frac{E}{GDP}}$. The carbon curse means that we could have an increase in CO_2 emissions $\widehat{\frac{CO_2}{GDP}} > 0$, despite a decrease in the energy intensity ($\widehat{\frac{E}{GDP}} < 0$) or a decrease in the emission rate $\widehat{\phi_f} < 0$ (green innovations or technical progress). Finally, if the new fossil deposits are less emitting (discovery of gases whose exploitation replaces coal), the change in the energy mix reduces CO_2 emissions.

An important result to highlight is the interdependence of the components in this accounting relationship. The size of the fossil fuel sector $\frac{E_f}{E}$ probably influences the severity of environmental regulation. However, this consequence of fossils on regulation can be negative or positive depending on external parameters such as the level of development, the size of the country, and household preferences. This means that when fossil resources increase $\widehat{\frac{E_f}{E}} > 0$, emissions intensity can also increase $\widehat{\frac{CO_2}{GDP}} > 0$ or may decrease if the emission rate decreases $\widehat{\phi_f} < 0$ (due to stricter regulation and *green* technological progress) or if the energy intensity of the GDP decreases, for example.

This simple decomposition approach identifies a set of possible factors that explain the CO_2 intensity, but accounting for decomposition alone does not explain correlation much (*a fortiori* causality). Moreover, it is essentially descriptive and does not take into account other factors that may influence the results, such as corruption or weather. To do so, we test a broader explanation of the evolution of the CO_2 intensity empirically, using an econometric approach that includes the set of fundamental variables identified in the accounting decomposition, to which we add variables which are the subject of consensus in the literature. Basically, we go beyond simple accounting decomposition and estimate reduced-form equations that link the level of CO_2 intensity to fossil resource abundance and other determinants.[5]

[5] An empirical estimation of this decomposition (Ang's Divisia index for example) faces several methodological limitations and has been highlighted in many studies on the EKC. For a detailed presentation of the pros and cons of each approach, see De Bruyn (1997) and Stern (2002).

3 Data

This study explores the linkages among renewable energy, environmental policy stringency, weather conditions, corruption, technological level, population, natural resource abundance, and CO_2 emissions to assess the validity of the carbon curse. Thus, to conduct an in-depth analysis of this assumption, we rely on two databases. The first one allows us to test the validity of a carbon curse by looking at the effect of natural resource abundance on the carbon intensity at the macroeconomic level. In a second step, we use a country sector database to refine the results by disentangling the overall country effect. Indeed, the disaggregated sectoral data allow for testing 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. This approach of using two databases is not free of cost. To conduct a consistent analysis, we need to keep the same countries in our two datasets. But data availability at the sectoral level is restricted to OECD and BRIC countries and through time. As a result, we have a sample of 29 OECD and BRIC countries over the 1995–2009 period.[6] Consequently, our datasets only include developed and emerging countries.

A key variable for our study is the measure of the resource stock. Until now, the literature relies on proxies for natural resource abundance because of the lack of appropriate data. The most-used proxy for abundance is the Sachs and Warner variable, which corresponds to the ratio of natural resource exports to GDP (Sachs and Warner, 1995). We argue that this proxy is an appropriate measure of the resource dependence, but not of abundance and it is potentially endogenous when used in the resource curse literature. For our study, we rely on the *resource abundance* variable from the World Bank data series (1997, 2006, 2011). The value of a country's stock of a non-renewable resource is measured as the present value of the stream of expected rents that may be extracted from the resource until it is exhausted (Lange et al., 2018).[7] It avoids the 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 concerns for the World Bank studies. Nevertheless, one might argue that data availability is conditional to a country's technological level. But data on natural resource wealth are probably independent of local issues, and exogenous enough for our study. Especially, fossil and mineral deposits which we focus on have been quite well explored and estimated due to the broad economic benefits they may confer (Karl, 1997). Moreover, the commitment

[6] The country-level dataset covers the 1995–2014 period. We conduct the same analysis over this extended sample and obtain qualitatively unchanged results; see section 6.

[7] The fossil energy resources valued in the World Bank wealth accounts are petroleum, natural gas, and coal, while metals and minerals include bauxite, copper, gold, iron ore, lead, nickel, phosphate rock, silver, tin, and zinc.

of large multinational firms using a similar technical approach to collect their information regardless of the local political and technological conditions is conducive to the exogeneity of our resource stock variable.

Finally, the measure of resource abundance by the World Bank is innovative and gives a 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 fossil and mineral stock present in a country) in US$ for cross-country or panel datasets.

The economy-wide and sectoral datasets are described in subsections 3.1 and 3.2, respectively.

3.1 The country level dataset

The country-level dataset covers yearly observations for 29 countries over the full spectrum from resource-rich to resource-poor countries among OECD and BRIC countries for the 1995–2009 period. Overall, our sample accounts for almost 75% of the world CO_2 emissions. Hence, to assess the impact of resource endowment on CO_2 emissions, we collect variables that together cover relevant socioeconomic and weather factors. Nine variables for each country are taken into account.

Details and sources for these variables are given in Table A.1 in Appendix A. Anthropogenic CO_2 emissions, resource abundance, GDP per capita (PPP adjusted), population, and technological level approximated by the number of filed patents are taken from the World Bank. A patent is taken as an observation in the year in which it is filed in a national patent authority from the 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, 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 the environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on pollution or environmentally harmful behavior. 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). Finally, weather conditions are captured through cooling degree days (CDD) and heating degree days (HDD), taken from the Euro-Mediterranean Center for Climate Change. Heating and cooling degree days (HDD and CDD) index measure the heating and cooling needed 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.

3.2 Sector level dataset

A dataset of 28 countries[8] in 34 sectors of activity from 1995 to 2009 is built from the World Input-Output Database (WIOD) and World Bank database, which provides a solid basis for an insightful analysis of the heterogeneity of natural resources impacts on sectoral CO_2 emissions. The WIOD is based on the national accounts which have been released as part of the European Commission's 7th Framework Program. The WIOD database has two main benefits in comparison to earlier available data sources. First, data process harmonization techniques have been implemented to guarantee international comparability of data. This ensures data quality and minimizes the risk of measurement errors. Second, WIOD provides sectoral price deflators, the use of which makes it possible to preserve important information and the heterogeneity of sectors in relation to price dynamics. This represents an improvement over the use of aggregated national price deflators.

By aggregating the sectoral database according to ISIC-rev2 classification, we obtain seven sectors, which allow for interpreting and comparing our results easily.

We also retain the same variables as in the country-level database but use sectoral data when they are available and relevant. Sectoral anthropogenic CO_2, sectoral value added, and technological level are taken from the WIOD. Sectoral technology variable corresponds to the share, in percentage, of sector-specific working hours of high-skilled workers as compared to total sector-specific working hours. A relative increase in high-skilled working hours is considered to be equivalent to an improvement in sector-specific technology. The environmental policy stringency, natural resource abundance, and the weather and socio-demographic variables are independent of the level of analysis.

3.3 Descriptive analysis

Although all countries in our sample are at an advanced stage of development, there are still economic and environmental heterogeneities. Tables 1 and A.2 provide descriptive statistics by variable of interest, while Tables 2 and 3 present the averages by country over 1995–2009, which is the common period with the sectoral dataset.[9] For consistency between country-level and sectoral estimates, we present the descriptive statistics, and in subsequent sections, the estimations.[10]

[8]The countries are the same as in the country level database, except for Hungary because of the lack of data at the sectoral level.

[9]Table 1 shows the average of all variables for the 1995–2009 period and all countries. Table 2 shows the averages by country. The min and max of Table 1 are absolute minimum and maximum observed over all the data.

[10]Section 6 provides a robustness test of the country-level estimation over the extended period of 1995–2014.

Table 1: Summary statistics

Variable	Mean	SD	Min.	Max.
CO_2 Intensity (kg/US$)	0.33	0.16	0.11	1.07
Abundance (2005 US$)	$1.73.10^{11}$	$4.70.10^{11}$	1.10^{6}	$3.47.10^{12}$
Environmental policy stringency (0;6)	1.53	0.85	0.33	4.07
Heating degree days ($^{\circ}$.nb days)	11826.86	5650.36	0.02	23174.28
Cooling degree days ($^{\circ}$.nb days)	2318.94	2768.20	19.36	11921.01
Technological level (nb filed patents)	29273	74022	40	384201
Alternative (% total energy use)	12.27	11.57	0.16	50.73
Corruption (-2,5;2,5)	0.99	1.02	-1.13	2.59
Population (millions hab.)	135.6	294.9	3.6	1331.3

Table 2: Variable means by country (1/2)

Country	CO_2 Intensity (kg/US$)	Abundance (2005 US$)	Alternative energy (% of energy use)	Env. Stringency 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 (°.nb days)	Cooling DD (°.nb days)	Technological level (nb filed patents)	Corruption (-2.5;2.5)	Population (millions hab.)
Australia	4337	3095	2262	1.92	19.7
Austria	18494	531	2073	2	8.1
Belgium	11643	1112	604	1.36	10.4
Brazil	759	7000	3476	−0.03	179.5
Canada	20883	876	4221	2	31.4
China	10297	3527	71598	−0.43	1275.7
Czech Republic	16848	767	625	0.37	10.3
Denmark	12116	519	1599	2.44	5.4
Finland	21426	407	2116	2.44	5.2
France	12069	1177	13759	1.34	61.9
Germany	15262	810	47222	1.91	82.2
Greece	9117	3385	408	0.47	10.9
Hungary	14092	1348	778	0.57	10.2
India	1750	11296	3646	−0.39	1089.9
Indonesia	0.1	10710	204	−0.85	217.8
Ireland	10969	61	882	1.58	4.0
Italy	10984	1647	7968	0.44	57.5
Japan	8483	2600	351313	1.13	127.1
South Korea	10180	2126	90068	0.38	47.4
Netherlands	11729	416	2299	2.17	16.1
Poland	15959	999	2375	0.39	38.3
Portugal	5182	1317	168	1.19	10.4
Russia	21439	1085	22612	−0.91	145.4
Slovakia	16060	1082	214	0.24	5.4
Spain	10089	2652	2773	1.22	42.3
Sweden	17021	392	3321	2.27	9.0
Turkey	12926	2830	788	−0.25	65.0
United-Kingdom	11559	350	18967	2	59.7
United-States	11291	3109	177772	1.6	287.1

The average national CO_2 intensities of the GDP range from 0.15 (Brazil and Sweden) to 0.83 (Spain), while the share of alternative energies varies from 0.21% (Poland) to 47.12% (Sweden). Similarly, the corruption index ranges from -0.91 for Russia to 2.44 for Denmark and Finland (negative values denote high levels of corruption), and goes hand in hand with the distribution of environmental stringency. The technological level index is another important differentiation factor, with the largest value (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 counterintuitive way, Sweden and Brazil, for example, have the same CO_2 intensity while the latter is much richer in resources than the former. 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.

Belgium has nearly the same carbon intensity as Japan or the United Kingdom despite having much lower natural resource abundance over the period. There may be a historical influence in this case: Belgium was once a resource-rich country, but its fossil resources (mainly coal) have now depleted.

The heterogeneity of natural resource abundance indicates that the sample covers economies from natural resource-rich countries to natural resource-poor countries.

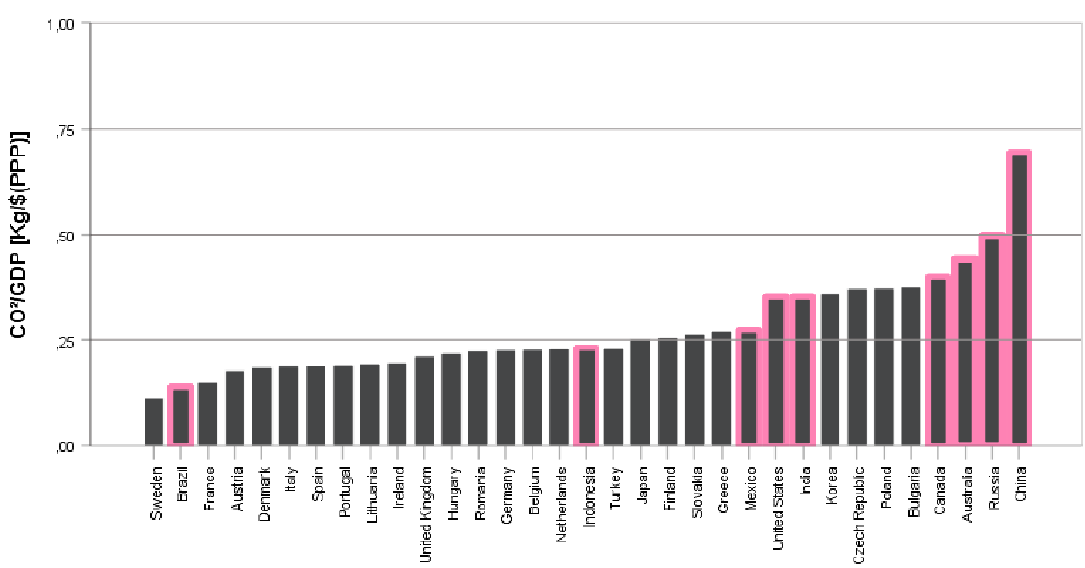

Figure 1: National carbon intensities in 2009. Resources-rich countries in pink.

To illustrate the overall relationship between natural resource abundance and energy intensity, Figure 1 ranks countries in our sample by increasing CO_2 intensity (per unit of GDP). The highlighted countries are rich in resources. Among the ten countries with the highest CO_2 intensity, six are resource-rich countries (highlighted in pink).[11]

A significant positive relationship can be easily seen in this figure. However, correlation itself is not a causal relationship. Atypical situations emerge, such as resource-poor countries with high CO_2 emissions (Korea, Czech Republic, Poland, Bulgaria), and the case of Brazil, a low emitter, although richly endowed with mineral and fossil resources. The impacts of natural resource abundance on CO_2 intensity remain unclear. The next section will further discuss these issues.

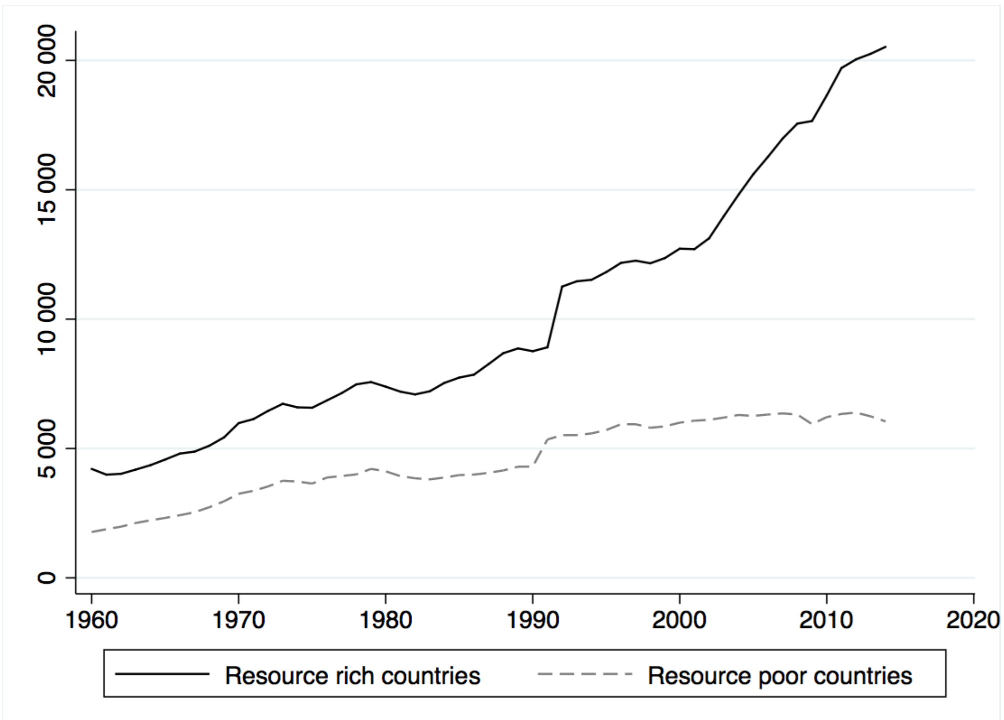

Figure 2: CO_2 emissions in OECD countries and BRIC.

To further investigate what appears in Figure 1, we split CO_2 emission levels on the basis of resource-rich and resource-poor countries. Figure 2 is somehow surprising and supports our intuition that countries rich in natural resources tend to cause pollution more than resource-poor countries. Since the early 2000s, both groups of countries show two opposite paths for CO_2 emissions. Resource-rich countries are on an increasing trend, while resource-poor countries are cutting or at least stabilizing their CO_2 emissions. This figure

[11]By restraining our panel to developed countries, we do not consider the OPEC countries which are both very rich in fossil resources and emit high levels of CO_2 (Friedrichs and Inderwildi, 2013). For the clustering between resource-rich and resource-poor countries, see footnote 11.

suggests that the debate on climate change mitigation should rather focus on a comparison of resource-rich countries versus resource-poor countries than the classic developed-country versus developing-country debate.

Like in Friedrichs and Inderwildi (2013), Figure 3 plots decarbonation achieved in the observed countries, defined as the reduction in CO_2 intensity over time, against average economic growth rates. Resource-rich countries are represented by circles while resource-poor countries are represented by triangles. Only one country (Indonesia) exhibits an emission intensification during the period; that is, a negative decarbonation (in red, below the horizontal line). The rest of the countries form two groups: above the 45% line, decarbonation is linked to emission reduction (green triangles), while below this line, decarbonation occurs together with emission increase (yellow triangles and circles).

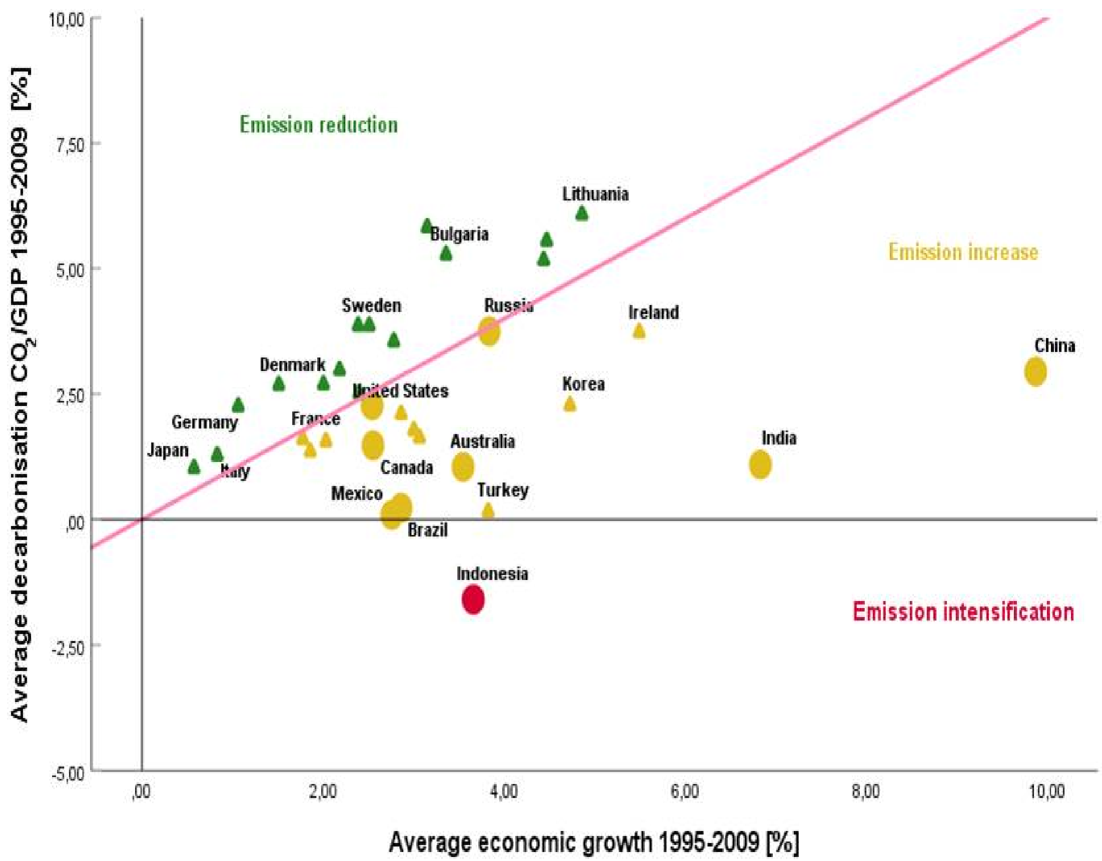

Figure 3: Carbon trajectories represented by the average annual increase or decrease in carbon intensity against average economic growth rates between 1995 and 2009.

We observe that all resource-rich countries emit more CO_2 despite the decrease in their emission rate, together with some other countries. Only resource-poor developed countries are above the 45% line, which can be interpreted as evidence in favor of a decreasing phase of an EKC. On the contrary, below the 45% line, countries are either still in the ascending phase of a possible EKC (for emerging countries) or never experienced an EKC but witnessed only ever-increasing emissions (developed countries like the United States or Australia).

A sectoral presentation of the data is provided in Figures 4.a to 4.c. The three main sectors presented are mining and utilities, services, and transport and communication. The CO_2 intensity of the sector is represented according to its share in the country's GDP. Large solid black circles are associated with resource-rich countries, while small black circles represent resource-poor countries. With the notations adopted in Equation 2, these figures allow to compare the sectoral contributions of sector i to national carbon intensity across countries, by plotting $\phi_{ih}.U_{ih}.I_i$ related to S_i.

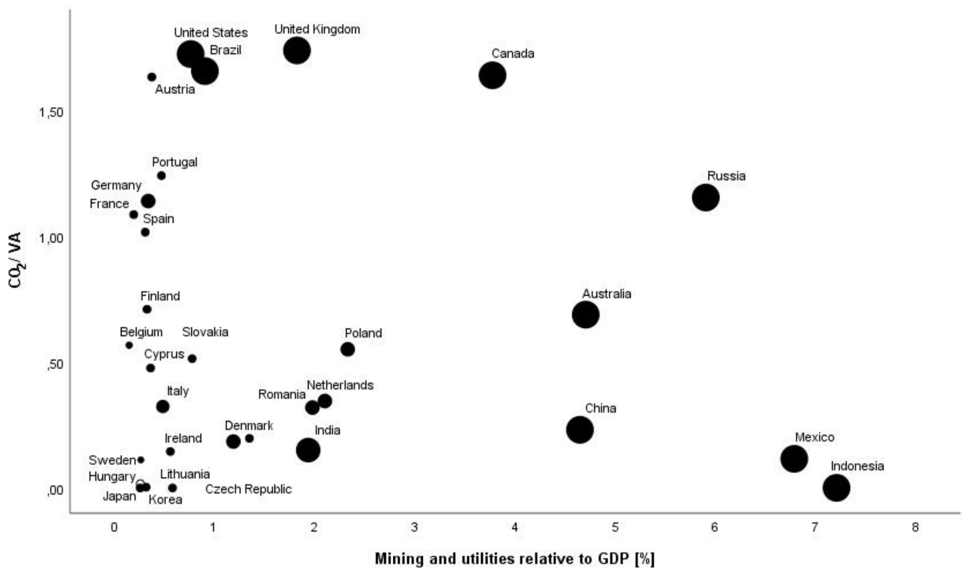

Figure 4.a: Sectoral carbon intensity and share of sector (Mining) in the economy

Figure 4.b 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. We observe some evidence of spillover effects. For a given country, a high CO_2/VA rate in the mining sector (Figure 4.a) is also associated with a high ratio in the services sector (Figure 4.b).

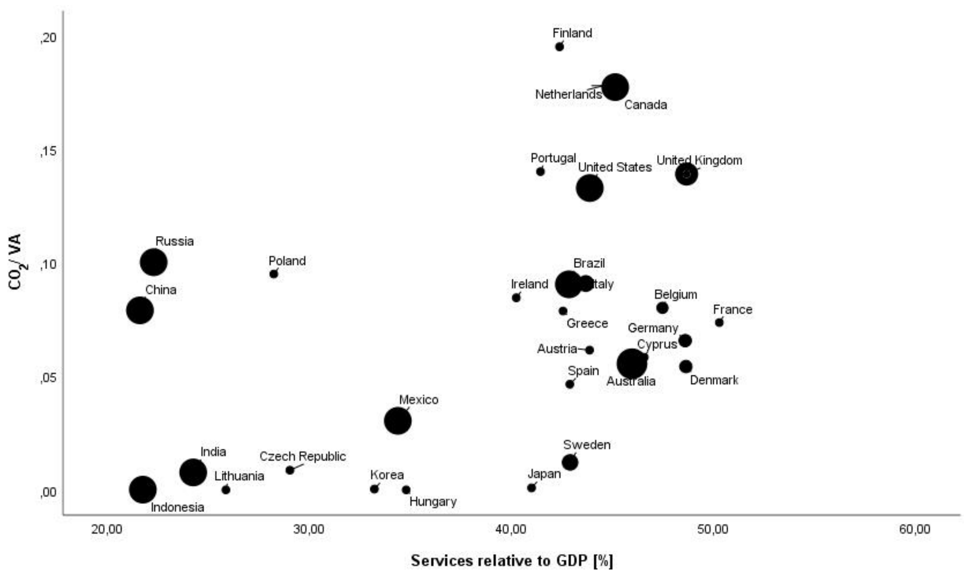

Figure 4.b: Sectoral carbon intensity and share of sector (Services) in the economy

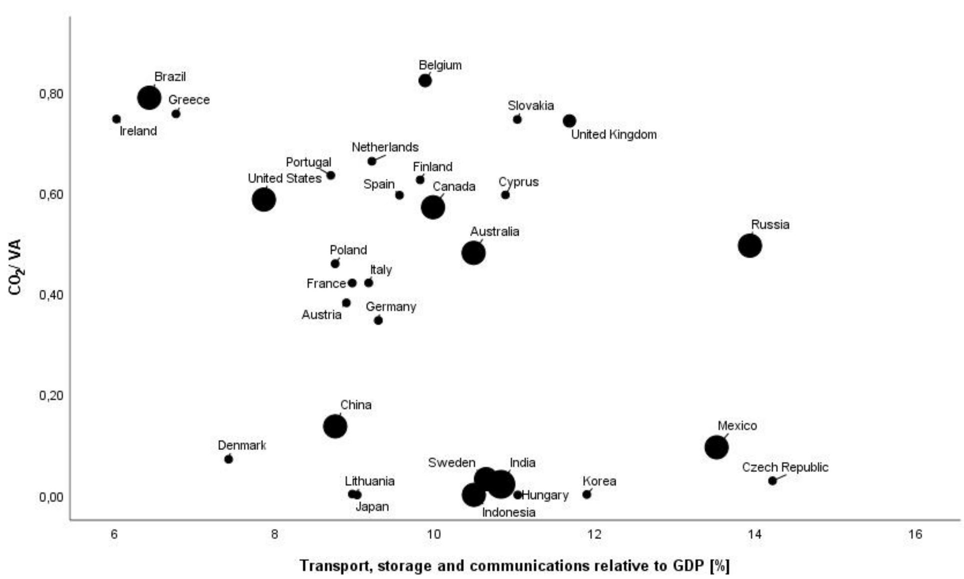

Figure 4.c: Sectoral carbon intensity and share of sector (Transports) in the economy

4 The empirical model

This section first presents the methodology used for estimates at the national level. We, secondly, present the sectoral approach.

4.1 Country wide estimation

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

$$(CO_2/GDP)_{it} = \beta_0 + \beta_1 Abundance_{it} + \beta_2 Abundance^2_{it} + \beta_3' X_{it} + \alpha_i + \nu_t + \varepsilon_{it} \quad (4)$$
$$i = 1, .., 29 \ ; \ t = 1, .., 15,$$

where the variable CO_2/GDP denotes CO_2 emissions intensity measured as emissions per GDP (kg per PPP \$ of GDP) in country i at time t. *Abundance* represents natural resources. It tries to capture any potential non-linear effect of natural resources on CO_2 intensity. Thus, 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 six control variables used in the literature to explain the CO_2 intensity. They can be divided into 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, the technological level, and the level of corruption. The second set includes weather variables (heating degree days and cooling degree days). Finally, α_i is the individual fixed effect that captures 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 diminishes endogeneity concerns related to omitted variables. Furthermore, all the variables are in a natural logarithm except corruption.

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 (Hill Carter et al.,2012). However, a robust Hausman test specification rejects it (Wooldridge, 2002). Thus, we use a fixed effects model using the within estimator which is consistent even if the fixed effects are correlated with the independent variables. The within estimator corrects for heteroscedasticity and intragroup correlation. Knowing that CO_2 emissions may be correlated between countries, we rely on two well-known spatial 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 the 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 errors are robust to very general forms of cross-sectional "spatial" and temporal dependence when the time dimension becomes large. The results are provided in Section 5.

4.2 Industry specific estimation

Once the concept of a carbon curse has been confirmed at the macroeconomic level, we use sectoral analysis to disentangle the overall effect of resource endowment on CO_2 emissions. We investigate whether resource-rich countries pollute more than resource-poor countries in all sectors. In other words, are there any spillover effects of carbon-intensive production processes to all sectors of the economy? Obviously, we expect the level of pollution in the mining sector to be higher in resource-rich than in resource-poor countries. However, is it still true for the other sectors? Firstly, we need to distinguish at least two groups of countries: resource-poor and resource-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 clusters to find is explicitly chosen. We set it at two, given the relatively small size of our sample (see subsection 3.2).[12] Second, we estimate the following panel data model on each sub-sample and compare the results:

$$(CO_2/VA)_{ijt} = \sum_{j=1}^{7} \beta_{1j}(Abundance_{it} * dummy_j) + \beta_2' X_{it} + \beta_3' X_{ijt} + \alpha_i + \delta_j + \theta_{ij} + \delta_{jt} + \nu_t + \varepsilon_{ijt} \qquad (5)$$

$i \in I_R, I_P$ where I_R (resp. I_P) is the subset of resource-rich (resp. resource-poor) countries

$j = 1, .., 7$; $t = 1, .., 15$.

[12] Data clustering according to Gan et al. (2007), also known as cluster analysis, is a process of forming groups of objects, or clusters, such that objects in one cluster are very similar and objects in different clusters are dissimilar.

We also use K-Medians clustering which is a variation of K-means clustering where, instead of calculating the mean for each cluster to determine its centroid, one calculates the median. This has the effect of minimizing error over all clusters with respect to the 1-norm distance metric, as opposed to the square of the 2-norm distance metric (which K-means does). In practice, K-means is easily affected by outliers. K-medians is robust to outliers and results in compact clusters.

In the above equation, $(CO_2/VA)_{ijt}$ stands for CO_2 emissions per dollar of value added to 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 the Environmental Policy Stringency Index (EPS), population, corruption, weather 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 effects which are α_i, δ_j, and θ_{ij}, respectively. Thus, to test if the effect of the resource endowment is different by sector, we introduce an interaction term between natural resources and sectoral dummies variable. Finally, all variables are in a natural logarithm except for corruption. We use the fixed effects estimator and use the same routine as in the country-wide estimation.

5 Estimation results

5.1 Country wide estimation

Our main model regresses CO_2 intensity on natural resource abundance, incorporating auxiliary variables to assess whether this relationship fits an ever increasing, decreasing, U-shaped or inverted U-shaped pattern. First, we estimate a random effects model and its results validate the existence of U-shaped behavior. Table 4 reports results and several tests: *i)* the F-test for individual effects tests the null of $\alpha_i = 0,\ \forall i$ in equation (4); *ii)* the Breusch-Pagan test for random effects tests the null of $Var(\alpha_i) = 0$ in equation (4); and *iii)* the Hausman test of fixed effects versus random effects strongly rejects the random effects model. Therefore, to alleviate heterogeneity bias, we rely on a fixed effect model and check for the presence of cross-sectional dependency. Accordingly, we perform various standard tests for cross-sectional dependence proposed by Pesaran (2004) and Frees (1995) and implemented in STATA by De Hoyos and Sarafidis (2006). Test results are reported in Table 4 and strongly reject the null hypothesis of cross-sectional independence. Hence, the Driscoll–Kraay estimation is employed, by which the standard error estimates are robust to general forms of cross-sectional and temporal dependence (Hoechle, 2007). Our main interpretations focus only on this estimation strategy.

The results are reported in column (3) of Table 4. The estimated coefficients remain unchanged and highly significant when we correct for spatial correlation. On average, all else being equal, a rise of 1% in the share of alternative energy results in 0.13% lower CO_2 intensity. This result indicates that CO_2 emission can be mitigated by increasing renewable energy usage, which is consistent with existing studies

Table 4: Country wide estimation results

Model	Random effects (1)		Fixed effects (2)		Fixed effects Driscoll-Kraay estimator (3)	
Abundance	-0.138**	(-2.00)	-0.095*	(-1.53)	-0.095***	(-3.34)
Abundance^2	0.003*	(1.88)	0.002	(1.46)	0.002***	(3.76)
Alternative Energy	-0.130***	(-3.81)	-0.141***	(-4.53)	-0.141***	(-6.46)
Stringency	-0.072**	(-2.42)	-0.070**	(-2.69)	-0.070***	(-3.24)
Heating DD	0.011	(0.54)	0.005	(0.30)	0.005	(0.16)
Cooling DD	0.013	(1.23)	0.020**	(2.23)	0.020	(1.09)
Technological level	0.080**	(2.66)	0.067**	(2.62)	0.067***	(9.41)
Corruption	0.044	(1.37)	0.037	(1.08)	0.037	(1.30)
Population	0.041	(0.62)	0.776**	(2.25)	0.776***	(6.15)
Constant	-1.018	(-0.76)	-14.164**	(-2.33)	-14.164***	(-6.75)
Observations	401		401		401	
Number of countries	29		29		29	
	F-test for individual effects					
F(28,349)	284.13 [0.000]					
	Breusch Pagan test for random effects					
$\chi^2_{(1)}$	1978.64 [0.000]					
	Hausman test of fixed effects versus random effects					
$\chi^2_{(15)}$	555..472 [0.000]					
	Pesaran's test of cross sectional independence					
	7.183 [0.000]					
	Frees' test of cross sectional independence					
	4.563 [0.000]					

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

(Ben Jebli et al., 2016). The relationship between Environmental Policy Stringency (EPS) and carbon emissions is negative and significant at the 1% level. Keeping other things constant, a 1% increase in Environmental Policy Stringency decreases CO_2 intensity by 0.07%. This direct effect on CO_2 might reflect the impact of new or stricter command and control instruments, even though our model does not allow to assess direction causality[13]. Given that an increase in stringency is generally preceded by a political debate, such an increase may be anticipated in advance. Hence, it is little surprise that the effect can be observed contemporaneously.[14] In addition, the direct effect of 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). As we use a proxy for the technological level (filed patents), that includes both green

[13]However, we have checked the causal relationship among panel variables, based on the Dumitrescu and Hurlin (2012) test and found that the environmental policy stringency variable Granger-causes carbon intensity but that there is no Granger-causality in the other direction.

[14]The results (available upon request) 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 benchmark model.

and standard technologies, our results suggest that new technologies are not necessarily less emitting than older ones. A 1% increase in population size leads to a 0.77% increase in CO_2 intensity: A larger population results in increased demand for energy, industry and transportation. The estimated coefficients on weather variables (CDD and HDD) show no impact on CO_2 intensity. This result can be explained by the fact that we consider average annual temperatures, which leads to insignificant results. Corruption has no significant impact on our results. This may be due to the developed countries that are in our sample. Indeed, a survey by the OECD indicated that corruption was a common issue in both developed and developing countries, and, comparatively, it had greater effect on CO_2 emissions in developing countries than that in developed countries.[15]

Finally, we find that the linear and squared terms of natural resource abundance have a negative and positive effect on CO_2 intensity at the 1% significance levels, respectively. It clearly shows the existence of a U-shaped relationship between natural resource abundance and CO_2 intensity. In other words, there is a turning point in the relationship between CO_2 per unit of GDP and resource abundance (both expressed in natural logarithms), such that, before this point, the elasticity is negative, while it is positive beyond.

Therefore, we find a decreasing relationship between CO_2 intensity and abundance for relatively resource-poor countries (before the turning point). Counter-intuitively, this means that more resources reduce CO_2 intensity in these countries. This result reflects the complex nature of the determinants of CO_2 emissions: the characteristics of the energy-mix (U_{ih}) and the sectoral structure of the economy (S_i) are essential elements for some resource-poor countries. Thus, when comparing two resource-poor countries, one country may have more resources while emitting less CO_2 if the difference in abundance is due to less emitting resources (gas compared to coal, for example); the energy mix will probably be less polluting. For the same reasons (the change in the energy mix), the discovery of resources (shale gas, shale oil, or minerals) will not necessarily lead to an increase in emissions or even, increasing resources could be beneficial in terms of CO_2 emissions per unit of GDP.[16] In this case, the intuition of the mechanisms could be as follows. Resource-poor countries have little crowding out effect (low entry barrier for renewable energies for instance), and the diffusion of polluting practices to non-fossil sectors is still low. An increase in resources should not imply a structural change in production; CO_2 should remain constant while the production may increase significantly. The induced economic growth may accelerate investment in research and development, which contributes to improved energy efficiency and reduced carbon intensity. Moreover, for a given level of resources, a country with a larger service sector will emit less CO_2. These mechanisms (energy substitution in the energy mix and

[15] http://www.oecd.org/daf/anti-bribery/ConvCombatBribery_ENG.pdf

[16] Balsalobre-Lorente et al. (2018) obtain similar results for 5 European resource-poor countries (France, Germany, Italy, Spain, and the United Kingdom).

sectoral structure of the economy) are crucial in resource-poor countries, which confirms that these countries are not too dependent on their resources.

For resource-rich countries, we find a carbon curse: any increase in resources translates into an increase in carbon intensity. The scale effect, therefore, plays a major role, in addition to the likely rigidity of technologies and the sectoral structure of the economy, which can be explained by the country's dependence on its natural resources. Actually, resource-rich countries have developed specific industrial structures which are largely influenced by the natural resource endowment. Indeed, the abundance of natural resources leads to low prices of resources, which results in high extensive and inefficient energy consumption patterns and low emissions efficiency (Adom and Adams, 2018; Yang et al., 2018). The role of the sectoral structure in CO_2 emissions is examined in the next section.

Our main conclusion is that the relationship between resources and carbon intensity is not monotonous. This relationship is decreasing for resource-poor countries, increasing for resource-rich countries, and ambiguous for intermediate countries. The carbon curse is, therefore, a somewhat more complex phenomenon than Friedrichs and Inderwildi (2013) suggest and does not affect all countries equally, specifically, those with few resources. Our study confirms that for a resource-rich country, it is difficult to avoid the carbon curse, perhaps even more difficult than avoiding the resource curse, in general. While one of the standard causes of the resource curse is the low quality of the institutions or the level of corruption, the carbon curse is clear for the resource-rich countries in our sample; corruption does not play any significant role in our result. Indeed, our sample confirms the existence of a carbon curse even though it does not include countries facing the resource curse.

5.2 Industry country specific estimation

To further investigate the complexity of the carbon curse highlighted at the national level, we rely on a country-sectoral analysis. This multilevel analysis provides economy and sector-specific coefficients for variables of interest, which forms the basis of a more detailed study on the heterogeneous effects of natural resource abundance on sectoral energy intensity. To do this, we group the countries according to their level of abundance using the K-means method. The two groups obtained are as follows:

- resource-rich countries: Russia, China, United States, Canada, Australia, India, Brazil, and Indonesia.
- resource-poor countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Netherlands, Poland, Portugal, Slovakia, Spain, Sweden,

Turkey, and the United Kingdom.[17]

The results are shown in Table 5.[18]

Table 5: Industry country estimation results

	Fixed effects			
	Resource-rich		Resource-poor	
Agriculture_abund	0.115	(1.02)	-0.056**	(-2.49)
Transport_abund	0.512***	(3.38)	-0.091***	(-3.96)
Manufacturing_abund	0.515***	(4.97)	-0.049***	(-3.25)
Construction_abund	-0.227	(-1.38)	0.057***	(2.62)
Electricity_abund	0.439***	(2.98)	0.084***	(3.32)
Mining_abund	0.863***	(4.97)	0.072	(1.07)
Service_abund	0.566***	(4.00)	0.014	(0.85)
Stringency	-0.046**	(-2.16)	-0.015	(-0.57)
Technological level	-0.054	(-1.33)	0.037	(1.36)
Corruption	0.052	(1.11)	-0.005	(-0.17)
Population	-0.065	(-0.15)	0.184	(0.64)
Heating DD	-0.024	(-0.85)	0.387***	(3.60)
Cooling DD	0.015	(0.20)	0.014	(0.80)
Observations	805		1960	
Number of countries	8		21	
Within R^2	13.81%		4.11%	
F statistic	F(13, 626) = 7.21 [0.000]		F(13, 1697) = 5.69 [0.000]	

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

The results show the heterogeneous impacts of natural resources endowment on sectoral energy intensity across sectors but also across the two groups of countries. For resource-rich countries, the positive relationship between natural resources and sectoral energy intensity can be clearly seen except in the agricultural and construction sector. As expected, the highest elasticity comes from the mining sector. On average, a 1% increase in natural resources endowment leads to a 0.86% increase in mining sectoral energy intensity. When it comes to the heterogeneous effects across service and non-service sectors (elasticities of transport (0.51), electricity (0.44), manufacturing (0.51), and services (0.57)), we find that the impacts of natural resource abundance in increasing sectoral energy intensity are quite similar between the services and non-services sectors. This was less expected. Spillover effects of the influence of abundance are, thus, occurring towards less resource-intensive sectors. Indeed, depending on resource advantages, resource-based countries have

[17] Both methods (K-means and K-medians) give the same groups of countries except for the United Kingdom that becomes a resource-rich country with K-medians method. However, the overall results do not change even when the United Kingdom is considered as included in the natural resource-rich category.

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

developed compatible industrial structures (Shi, 2013). Most of the industries in these countries are likely to be characterized by high energy and emissions intensities. The abundance of natural resources leads to low prices of resources. This has led to high extensive and inefficient energy consumption patterns and low emissions efficiency (Adom and Adams, 2018; Yang et al., 2018) because of lower willingness to invest in resource-saving technologies and equipment (Shi, 2014). In addition, non-resource-intensive sectors are closely attached to the resource-intensive ones, and, as a result, it may lead to resource dependence, which worsens the carbon emissions efficiency in non-resource-intensive sectors (like services). Overall, the extensive use of resources will inevitably lead to a decline in carbon emissions efficiency because companies' behavior in resource-based countries is different from those in other regions. Finally, the Environmental Policy Stringency significantly reduces CO_2 intensity in resource-rich countries.

For resource-poor countries, the empirical findings show opposite results, which confirms the heterogeneous impact of natural resource abundance across the two groups of countries. The relationship between natural resources and sectoral energy intensity is mixed. On average, a 1% increase in natural resources endowment leads to a 0.08% increase in electricity sectoral energy intensity which is five times smaller than for resource-rich countries. Interestingly, there is a clear negative relationship between natural resources and CO_2 intensity of manufacturing, transport, and the agriculture sector. It can be caused by changes in energy efficiency in these sectors prompted by the rapid increases in energy prices between 2002 and 2009. Domestic policies may respond to the distortions due to energy price fluctuations; for example, energy price reforms (Feng et al., 2009; Yang et al., 2016; Zhao et al., 2010), tax policies on energy-intensive products and sectors (Price et al., 2011), and public funding and programs towards changing consumer behaviors regarding energy use (Allcott and Mullainathan, 2010). Weather conditions during heating days may increase carbon intensity in all sectors for resource-poor countries.

6 Discussion

In this section, we carry out several robustness checks, for which all results are shown in Appendix.

First, our estimated model relates the carbon intensity of GDP to abundance. Since the most emitting and resource-rich countries are also the largest countries of our sample, it is questionable whether it is sufficient to introduce the population variable as a control variable in our estimates. This is the reason why we also estimated the impact of abundance on emissions per capita, introducing GDP per capita as an additional explanatory variable in this case. Results are provided in Table A.3: the U-shaped curve is unaffected.

Second, Table 2 and Figure 1 show that Brazil, Russia, India, and China (the BRIC) are among the most resource-rich countries and are also the largest emitters (except Brazil). We, therefore, exclude these countries from our sample and estimate the model only for OECD countries. The results are clearly not qualitatively affected, even though the estimated coefficients for *Abundance* and *Abundance*^{2} are both lower than that for the whole sample (Table A.4). However, considering only long-established industrialized countries, we still obtain a U-shaped curve between carbon intensity and natural resource abundance. This U-shaped curve is only a little flatter than when BRIC countries are included.

Third, to assess whether some kinds of natural resources drive the results, we estimate the same relationship for each kind of natural resource taken separately: coal, oil, or natural gas (Table 6); fossil fuels and mineral resources (Table A.5).

Table 6: Country wide estimation – Type of fossil resources

Model	Coal		Oil		Natural Gas	
	Driscoll-Kraay estimator		Driscoll-Kraay estimator		Driscoll-Kraay estimator	
	(1)		(2)		(3)	
Abundance	0.000	(0.09)	-0.007**	(-1.98)	-0.015**	(-2.21)
Abundance^2	0.000	(0.19)	0.001***	(3.08)	0.001**	(2.25)
Alternative Energy	-0.143***	(-6.54)	-0.145***	(-9.40)	-0.139***	(-5.90)
Stringency	-0.077***	(-3.55)	-0.078***	(-3.30)	-0.070**	(-2.86)
Heating DD	0.003	(-0.10)	0.002	(0.06)	0.004	(0.14)
Cooling DD	0.021	(1.12)	0.020**	(2.19)	0.020	(1.13)
Technological level	0.069***	(10.18)	0.067***	(10.88)	0.063***	(9.14)
Corruption	0.033	(1.13)	0.033	(1.57)	0.034	(1.28)
Population	0.819***	(5.81)	0.799***	(12.96)	0.792***	(6.19)
Constant	-16.106***	(-6.50)	-15.814***	(-15.37)	-15.666***	(-6.89)
Observations	401		401		401	
Number of countries	29		29		29	

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

The U-shaped curve is clearly confirmed for oil and natural gas but not for coal, which indicates that coal is not the main cause of carbon intensity in our sample.[19] A country could have large coal reserves but not exploit them, and could use nuclear plants to produce electricity. In this case, any increase in coal abundance would not affect CO_2 emissions. We also estimated models including either only mineral resources, only fossil resources or simultaneously oil & gas versus coal abundance (Table A.5). Intuitively, mineral resource abundance does not significantly impact carbon intensity of GDP. As for fossil resources

[19]Indeed, the descriptive statistics show that coal reserves are declining in most of the countries in our sample.

abundance, Table A.5 corroborates results of Table 6 regarding the major role of oil and natural gas in driving the carbon curse.

We check whether the results obtained at the macroeconomic level over the restricted period compatible with sectoral data availability still hold over the extended period of 1995–2014. As shown in Table A.6, the U-shaped curve still appears.

Finally, the timing of resource discoveries is likely to impact firm behavior and change sectoral and national carbon intensities. In theory, new discoveries are expected to decrease prices. Do firms immediately respond to announcements of new reserves or do they wait until prices actually change when those reserves come into production? If the latter is the case, there are some lags between increases in abundance and carbon intensity, as was shown for the impact of abundance on GDP (Arezki et al., 2017) and on the real exchange rate (Harding et al., 2020). More generally, the impacts of new discoveries on energy prices, and hence on firm behavior are ambiguous, because of general equilibrium effects. Indeed, new discoveries influence prices, and hence extraction path, FDI (Toews and Vézina, 2017), GDP, investments and R&D in the resource sectors, which in turn influence prospection and discoveries (Anderson et al., 2018). In the same time, oil discoveries increase the risk of internal armed conflict (Lei and Michaels, 2014) and deteriorate democratic institutions (Tsui, 2011), associated with lowered income expectations. These important questions deserve attention and should motivate further studies, including assessment of the impacts of discoveries on firms' energy intensity.

7 Conclusion

In this study, we empirically assess the carbon curse assumption. We demonstrate that the relationship between CO_2 emissions per unit of GDP and abundance in natural resources is U-shaped. The carbon curse appears only after the turning point, beyond which countries rich in coal, oil, gas, and minerals emit more CO_2 per unit of GDP compared with countries where natural resources are relatively rare. The carbon curse is, therefore, a somewhat more complex phenomenon, for which the nature of resources owned and spillover effects in the whole economy play a crucial role. We then test the consequences of abundance on the sectoral emissions for two groups of countries, depending on their resource endowments. We confirm that a country rich in fossil and mineral resources pollutes more in resource-related sectors. We also find that CO_2 intensity is positively and highly impacted in all other sectors, even in the services sector. That is explained not only by a composition effect (characterized by a predominance of the mining sector in the GDP) but also by spillover effects (due to a weak environmental policy) and, potentially, a crowding out effect (likely induced by barriers to the development of renewable energies, imposed by the fossil energy sectors). Further research may address the potential links between these pollution mechanisms and the characteristics of the resources (natural gas, non-conventional oil, coal, and mineral resources, among others).

These results suggest that resource abundance should be a key variable in climate policy negotiations. Taking it into account would make it possible to target the main countries to be regulated better. Indeed, rather than focusing on a debate on the efforts to be made, which pits developed countries against developing countries, it would be more appropriate to group and coordinate the countries according to their natural resources endowment.

Appendix

Table A.1: 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)	Kaufman et al. (2010)
Population	Millions hab.	https://data.worldbank.org/indicator/SP.POP.TOTL

Table A.2: Dynamic country-aggregate statistics

Variable	Mean [1995-1999]	Mean [2000-2004]	Mean [2005-2009]
CO_2 Intensity (kg/US$)	0.38	0.33	0.29
Abundance (2005 US$)	$0.79.10^{11}$	$1.46.10^{11}$	$2.77.10^{11}$
Environmental policy stringency (0;6)	1.02	1.41	2.18
Heating degree days (°.nb days)	12065.19	11780.87	11634.51
Cooling degree days (°.nb days)	2248.07	2350.10	2358.65
Technological level (nb filed patents)	23735.31	29193.40	34849.19
Alternative (% total energy use)	11.86	12.33	12.61
Corruption (-2,5;2,5)	1.03	0.99	0.95
Population (millions hab.)	128.9	135.7	142.1

Note: Means are computed over the period following the measurement of the variable Abundance.

Table A.3: Country wide estimation – Dependent variable CO_2 per capita

Model	Random effects		Fixed effects		Fixed effects Driscoll-Kraay estimator	
Abundance	-0.141**	(-2.13)	-0.141*	(-1.90)	-0.141**	(-2.52)
Abundance^2	0.003**	(1.98)	0.003*	(1.80)	0.003**	(2.39)
GDP_capita(PPP)	0.591***	(8.63)	0.545***	(7.48)	0.545***	(7.22)
Alternative Energy	-0.126***	(-3.65)	-0.130***	(-3.49)	-0.130***	(-7.68)
Stringency	-0.049**	(-2.49)	-0.045**	(-2.51)	-0.045***	(-3.32)
Heating DD	0.017	(0.93)	0.0003	(-0.03)	0.0003	(0.01)
Cooling DD	0.006	(0.54)	0.009	(0.75)	0.009	(0.90)
Technological level	0.133***	(5.86)	0.142***	(5.80)	0.142***	(12.06)
Corruption	0.065***	(2.64)	0.059**	(2.55)	0.059**	(2.32)
Constant	-3.65***	(-4.01)	-3.038***	(-3.40)	-3.038***	(-4.54)
Observations	401		401		401	
Number of countries	29		29		29	

	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
$\chi^2_{(15)}$	129.616 [0.000]
	Pesaran's test of cross sectional independence
	-2.459 [0.0139]
	Frees' test of cross sectional independence
	4.563[0.000]

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

Table A.4: Country wide estimation – OECD Countries only

Model	Random effects		Fixed effects		Fixed effects Driscoll-Kraay estimator	
	(1)		(2)		(3)	
Abundance	-0.127**	(-2.01)	-0.107**	(-2.08)	-0.107***	(-3.16)
Abundance^2	0.003***	(1.75)	0.003*	(1.87)	0 .003***	(3.00)
Alternative Energy	-0.140***	(-6.20)	-0.148***	(-8.04)	-0.148***	(-9.18)
Stringency	-0.067**	(-2.43)	-0.071***	(-2.94)	-0.071***	(-5.19)
Heating DD	0.351***	(4.40)	0.356***	(6.58)	0.356***	(6.08)
Cooling DD	0.032***	(3.90)	0.031***	(3.85)	0.031*	(2.01)
Technological level	0.081***	(5.17)	0 .078***	(4.75)	0.078***	(6.84)
Corruption	0.013	(0.39)	0.016	(0.45)	0.016	(0.58)
Population	-0.010	(-0.21)	0.515*	(1.75)	0.515***	(3.73)
Constant	-3.454***	(-2.75)	-12.569**	(-2.55)	-12.569***	(-6.08)
Observations	331		331		331	
Number of countries	24		24		24	
	F-test for individual effects					
F(23,284)	247.38 [0.000]					
	Breusch Pagan test for random effects					
$\chi^2_{(1)}$	1220.07 [0.000]					
	Hausman test of fixed effects versus random effects					
$\chi^2_{(15)}$	585.364 [0.000]					
	Pesaran's test of cross sectional independence					
	-2.638 [0.0084]					
	Frees' test of cross sectional independence					
	4.758 [0.000]					

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

Table A.5: Country wide estimation – Fossil vs mineral resources

Model	Fossil Fuels		Minerals		Oil & Gas vs Coal	
	Driscoll-Kraay estimator		Driscoll-Kraay estimator		Driscoll-Kraay estimator	
Abund. Fossil	-0.016***	(-3.58)	–	–	–	–
Abund. Fossil^2	0.001***	(3.53)	–	–	–	–
Abund. Minerals	–	–	0.002	(0.59)	–	–
Abund. Minerals^2	–	–	-0.000	(-0.74)	–	
Abund. Oil&Gas	–	–	–	–	-0.010**	(-2.03)
Abund. Oil&Gas^2	–	–	–	–	0.001**	(2.68)
Abund. Coal	–	–	–	–	-0.000	(-0.20)
Abund. Coal^2	–	–	–	–	0.000	(0.39)
Alternative Energy	-0.141***	(-6.86)	-0.143***	(-6.71)	-0.141***	(-5.94)
Stringency	-0.076***	(-3.47)	-0.079***	(-3.41)	-0.078***	(-3.12)
Heating DD	0.003	(0.10)	0.003	(0.11)	0.004	(0.11)
Cooling DD	0.021	(1.13)	0.021	(1.12)	0.020	(1.12)
Technological level	0.062***	(8.49)	0.071***	(10.18)	0.065***	(8.53)
Corruption	0.040	(1.41)	0.034	(1.15)	0.032	(1.15)
Population	0.855***	(6.71)	0.825***	(6.58)	0.805***	(5.85)
Constant	-16.818***	(-7.48)	-16.202***	(-7.39)	-15.940***	(-6.55)
Observations	401		401		401	
Number of countries	29		29		29	

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

Table A.6: Country wide estimation results over the 1995– 2014 period

Model	Random effects		Fixed effects		Fixed effects Driscoll-Kraay estimator	
	(1)		(2)		(3)	
Abundance	-0.101*	(-1.94)	-0.077	(-1.39)	-0.077***	(-4.15)
Abundance^2	0.003**	(2.07)	0.002	(1.44)	0.002***	(4.25)
Alternative Energy	-0.139***	(-5.69)	-0.150***	(-6.05)	-0.150***	(-7.96)
Stringency	-0.064*	(-1.92)	-0.066*	(-1.87)	-0.066***	(-2.99)
Heating DD	-0.009	(-0.35)	-0.065**	(-2.53)	-0.065	(-1.69)
Cooling DD	-0.007	(-0.40)	-0.011	(-0.61)	-0.011	(-0.63)
Technological level	0.083***	(2.97)	0.092***	(3.74)	0.092***	(7.32)
Corruption	-0.034	(-0.64)	-0.038	(-0.74)	-0.038**	(-2.52)
Population	-0.028	(-0.17)	-0.261	(-1.03)	-0.261	(-1.37)
Constant	-0.375	(-0.65)	-0.071	(-0.11)	-0.071	(-0.13)
Observations	519		519		519	
Number of countries	29		29		29	

Test	Statistic
	F-test for individual effects
F(28,463)	250.76 [0.000]
	Breusch Pagan test for random effects
$\chi^2_{(1)}$	3428.24 [0.000]
	Hausman test of fixed effects versus random effects
$\chi^2_{(20)}$	801.873 [0.000]
	Pesaran's test of cross sectional independence
	-2.501 [0.0124]
	Frees' test of cross sectional independence
	3.164 [0.000]

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

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