Carbon Curse and the National Oil Companies:

an empirical analysis of the conditional carbon curse with respect to the power of National Oil Companies

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Abstract

In this thesis, I estimate the existence of the relationship between oil and gas resource abundance and CO_2 emission intensity, the so-called carbon curse. Besides the original carbon curse hypothesis, I expand my model and test for conditional carbon curses with respect to the regulatory and the economic power of the National Oil Companies (NOCs) in a country. I work with country panel datasets across 131 countries from 1980 till 2013 and measure the hypothesis by using the two-way fixed effect model with Driscoll-Kraay standard errors. Results demonstrate that the carbon curse exists, and I find an inverted U-shaped relationship between resource dependency and national CO_2 emission intensity. I prove that the carbon curse exists only in countries with regulatory NOCs, but I am not able to provide evidence for the conditional carbon curse, considering the economic NOC power. My findings highlight the importance of incorporating resource dependency to the human-related CO_2 mitigation discussion and suggest some evidence that one of the most important oil market actors', the National Oil Companies' institutional setting has a key role in the existence of the carbon curse.

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1. Introduction

Greenhouse gas emission sharply increases since the pre-industrial times, becoming one of the main contributors to the alarming rate of global warming (Sims et al., 2007). Human-related factors, such as industrial production, growing energy demand and radically accelerating transportation are the main sectors that contribute to this increasing level (IPCC, 2014). All these sectors have one thing in common, they have high energy intensity, overall, two-thirds of the greenhouse gas emissions are related to energy creation (Lee, 2020). The energy sector is dominated by fossil fuels, in 2019 around 84% of the primary energy came from gas, oil, and coal (Ritchie, n.d.). Therefore, it is not a surprise that one of the most important goals in global climate agreements is to achieve energy transition from highly polluting fossil fuels to renewable energy, to curb down energy-related emission (IPCC, 2014) (UN, 2015). In my thesis, I investigate this human-induced channel of global warming. I examine the following research question: *how are carbon dioxide emissions (the most significant greenhouse gas) driven by the production of fossil fuels (precisely oil and gas) and how are human-made institutional and market environments influencing emission level in different countries*.

In environmental and energy policy literature a growing number of analyses are focusing on how human-related economic factors affect carbon dioxide emissions. Researchers use decomposition methods (like Kaya identities (Kaya, 1990)) and formulate empirically tested hypotheses, like the environmental kuznets curve theory (Grossman – Krueger, 1991) to understand the channels. The Environmental Kuznets Curve suggests that there is a relationship between economic growth and pollution, economic development is accelerating pollution until a given point, and then the effect reverts (Grossman – Krueger, 1991). In parallel, in development economics and political economics literature, the relationship between resource abundance and economic and institutional development is a widely discussed topic. According to the resource curse theory, even though resource abundance could be a lucrative sector, it often negatively affects countries' economic and political development (Sachs and Warner, 1995). To understand the direct relationship between fossil resource abundance and pollution, I will investigate the crossroad of the environmental kuznets curve and the resource curse theories, and I will empirically measure the direct relationship between resource abundance and pollution, exploring the so-called "carbon curse".

The carbon curse, first formulated by Friedrichs and Inderwildi (2013), suggests that there is a direct relationship between resources and pollution, more precisely fuels and emissions. The more fuel-rich a country appears to be the higher CO2 emitter it is seen to be. The theory claims that there are four potential channels behind this hypothesis, on top of the rather obvious extraction related channel large resource abundance could potentially crowd out other, less-polluting energy sources, could weaken the incentives to invest in energy efficiency and could support fuel consumption in a country (Friedrichs – Inderwildi, 2013 p.1357). Empirical analysis of this question is scarce so far, so, in my thesis, I will measure the carbon curse effect. Moreover, I will extend the regular literature and investigate one of the main actors', National Oil Companies' role they plan in bringing about what we call the carbon curse.

Fuel and gas extraction and production are highly concentrated in the hands of large National Oil Companies' (thereafter NOCs), around 75% of the total production is done by these enterprises (Tordo et al., 2011 p.XI). These companies have extremely large market powers and control over the production, but previously the role of NOCs in resource and carbon curse was not very well studied, mostly due to the lack of transparent data provisions. A recent study and dataset from Mahdavi (2020a, 2020b) suggest that market and institutional structures behind NOCs are varying between countries and if a NOC has regulatory power over the market, it causes higher levels of bribery. Therefore, I will incorporate the institutional and market environments of the NOCs into the carbon curse model, to test my conditional carbon curse hypothesis: Market and institutional setups behind national oil companies could amplify the carbon curse, *monopolistic NOC's and regulatory NOC's powers are amplifying the carbon curse effect*. The purpose of my thesis is twofold: first, I would like to measure the carbon curse empirically, and secondly, I would like to measure the conditional carbon curse with respect to the NOCs' power.

My empirical analysis is using panel data including 131 countries from 1980 till 2013. By combining a large oil and gas database from Ross and Mahdavi (2015) and the National Oil Companies database from Mahdavi (2020b) I can investigate my hypothesis. I will use a two-way fixed effect model with the Driscoll-Kraay standard error measure to correct for the cross-country interdependence above the heteroscedasticity and autocorrelation. As a result, I find the existence of the carbon curse effect and accept my hypothesis stating that regulatory NOCs amplify the carbon curse effect, in fact, I only find the existence of the carbon curse in countries with regulatory NOC. However, I am not able to accept the existence of the conditional carbon curse to monopolistic NOCs.

The rest of the paper will be structured as follows: in **Section 2** I will review the theories and empirical literature related to the carbon curse, namely, the literature covering the economic kuznets curve and the resource curse, and I will also discuss existing NOCs' related findings. In **Section 3** I will introduce the carbon curse theory, review the literature, and discuss my extended conditional carbon curse model. Built on the literature review and the theoretical framing, I will present my empirical model in the **Section 4**. After, in **Section 5,** I will introduce my data and the descriptive statistics findings, while **Section 6** will contain my results and several empirical checks and robustness estimations. In **Section 7**, I will conclude by presenting the limitations of my thesis, and by providing some proposals for potential future works.

2. Human-Related CO2 Emission Literature and the Resource Curse Literature

In the following section, I will provide an overview of the main theories which contribute to the carbon curse hypothesis, and I will also summarize the empirical results of the existing literature. Since carbon curse theory is at its early stage of theoretical and empirical testing, thus briefly discussing related literature is important to formulate my model precisely.

2.1. CO2 Emission and Socio-Economic Factors

2.1.1. Theoretical Foundations of the EKC

As one of the first CO2 emission models, Kaya identity, formulated by Kaya (1990) decomposes CO2 emissions, looking at GDP per capita, total energy consumption per capita and fossil-fuel based energy consumption per capita. Decomposition suggests that an increase in these factors could accelerate emissions. Although this is a valuable concept to understand potential factors behind pollution and it is widely used in practical environmental policymaking (Hwang et al. 2020) (IPCC, 2000), this method is merely a starting point to understand the causal relationship behind increasing CO2 emissions. Similar to the Kaya identity, the STIRPAT model also captures the level of the emission (Dietz – Rosa, 1997). This model emerged from the IPAT identity which measures the CO2 (I – environmental impact) as the multiplication of a population (P), affluence (A), and technology (T) (Dietz – Rosa, 1997 p.175). The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model was first formulated by Dietz and Rosa (1997) and allows for more flexibility, therefore creating a theoretical framework allowing to add other variables to the model.

The most influential theory built on these decompositions is the environmental kuznets curve theory (thereafter EKC). The theory claims an inverted U-shape relationship between economic growth and emission, which could be the result of the scale, composition, and technological effects (Krueger & Grossman, 1991 p.3-4). According to the hypothesis, at the beginning of a country's development, a larger scale production will cause accelerating emissions, due to the increasing economic activity. However, after a certain level of development, there is a shift from the scale effect to the composition effect (composition effect: change from industrial production to service sector) and to the technological effect (technological effect: economic development leads to environment more friendly policies), resulting in a decrease in pollution per capita (Sarkodie – Strezov, 2018 p.3 – 5). Throughout the years, some additional factors and channels have been identified, these channels help to sophisticate EKC and specify the factors behind human-related emissions (Mardani et al., 2019).

2.1.2. Empirical EKC Literature Review

Moving forward from the theoretical foundations of the CO2 emission analysis towards the empirical research, according to Mardani et al. (2019), a rapidly growing number of empirical papers focus on the relationship between socio-economic factors and emission, extending the Environmental Kuznets Curve theory. Papers are using per capita emission, mostly focusing on CO2 emissions, although sometimes researches also include other pollution measures (Stern – van Dijk, 2017) or use pollution indexes (Al-Mulali - Ozturk, 2015) (Mavragani et al., 2016).

Similar to the original paper from Grossman and Krueger (1991), analysis from Stern and van Dijk (2017) or Rofiuddin et al. (2019) and large parts of the literature suggests an inverted U-shape relationship between economic development and environmental degradation. However, the empirical findings regarding the shape of the curve are somewhat mixed: some recent papers define N-shape or monotonic relationships. For example, Balsalobre-Lorente et al. (2018) claim to identify an N-shape relationship in EU5 countries from 1985 – 2016. Özokcua and Özdemir (2017) also find an N-shape relationship by examining panel data from 1980 – 2010 on OECD countries, and an inverted N-shape relationship by investigating 52 emerging countries. Other papers (Stern & van Dijk, 2017) (Holtz-Eakin & Selden, 1994) even propose monotone increasing positive correlation between economic development and pollution. Although there is a debate about the exact shape of the EKC, what is important moving forward is that economic development, at least until some stage of level of development, intensifies pollution.

Besides and behind the direct growth-related impact, more and more studies focus on other channels that affect CO2 emission. First, researchers suggest that decreasing EKC partially comes from the effect of trade openness and diversification. Liu et al. (2019) use a panel dataset from 125 countries between 2000-2015, according to a fixed and random effect model with Driscoll-Kraay standard error export diversification helps to moderate CO2 emissions. Cialani (2017) claims, by using Granger causality estimation in panel data, that there is a causal relationship between trade and per capita CO2 emission.

The second potential channel is energy consumption. Mardani et al. (2019) summarize case studies in several countries using a time-series framework and suggest a positive relationship between energy consumption and emission. For example, a causal relationship between economic growth and energy consumption on the short and long term was found in Portugal (Shahbaz et al., 2011).

Recent papers focus on the potential positive outcome of renewable energy on decreasing pollution. Somewhat contradicting, when Al-Mulali et al. (2015) investigate the renewable effect in Latin America and the Caribbean regions from 1980 to 2010 find no significant connection between renewable energy consumption and CO2 emission on the long run, even though Granger-causality provided causal connection result. However, Chiu and Chang (2009) use a panel dataset from 30 OECD countries and find that above a given threshold, renewable energy usage could decrease pollution. Bento and Moutinho (2015) investigate the connection between renewable and non-renewable electricity production and CO_2 emission in Italy between 1960 – 2011 and find that renewable energy production influences CO_2 emissions negatively.

Other parts of the literature focus on institutional factors. Mavragani et al. (2016) look at 75 countries and find a positive relationship between institutional quality and the environmental performance index. Sulemana et al. (2016) find mixed effect, democracy non-significantly affected CO_2 emission in 47 countries in Africa and an OECD sample from 1990 to 2010, although with alternative pollution measures the effect is significant measured on the African sample. Usman et al. (2019) analyze this same association in India between 1971 and 2014 and find negative causality between democracy and CO_2 emission on the short run, but an insignificant connection on the long run. Results are mixed, but in general, the theory suggests bad institutions result in inefficiencies and greater environmental degradation.

Some other channels were also tested, like the role of tourism which seems to have a positive relationship in terms of emission (Lee & Brahmasrene, 2013) and the positive effect of financial investment (mainly measured with FDI) on pollution was also tested (Al-Mulali, 2012). Finally, a few of the empirical papers (Bekun et al., 2019) (Ike et al., 2020) (Neumayer, 2002) (Balsalobra-Lorente et al., 2018) include non-renewable fossil resource (mainly oil and gas) as an independent variable, but I will discuss these implicit carbon curse papers in section *2.3.2*. in a more detailed manner.

Regarding the scope of the above-presented papers, part of the studies focusses on global or country group level, using panel datasets and methodologies, while the other part of the relevant literature targets specific countries and investigates relationships in a time-series setup (Mardani et al., 2019). Methodologies of the analyzes, in the case of panel models, are the fixed effect, random effect and part of them is corrected by Driscoll-Kray method (Rofiuddin, 2019)

(Liu, 2019) (Hashmi & Alam, 2019) (Sulemana et al., 2010) (Özokcua & Özdemir, 2017). The country-specific analysis (targeting only one or a few countries) uses time estimations, measures short- and long-term relationships with the Granger causality test, error correction models, and autoregressive models (Lee & Brahmasrene, 2013) (Cialani, 2016) (Shahbaz et al., 2011) (Bento et al., 2015) (Al-Mulali et al., 2015) (Usman et al., 2019).

Although there are some differences between the carbon curse literature and the literature related to EKC (as I will highlight later), understanding how these papers utilize panel data structure and what types of modeling frameworks they use are important steps in understanding the carbon curse. From the presented literature it is obvious that a relationship between human activity and emission exists, however it is a complex phenomenon, thus it is important to interpret any results with a great degree of cautiousness. Regarding the carbon curse, standard human-related pollution literature rarely focuses on the potential fossil production effects, even though a different literature, the resource curse theory suggests a negative effect of relying on such non-renewable energies. I will briefly discuss this theory in the following subsection.

2.2. The Resource Curse

2.2.1. Theoretical Foundation of the Resource Curse

The second theory related to the carbon curse is the resource curse theory. As a pioneer in this topic Sachs and Warner (1995) proved the curse in their early paper and suggested that resource-abundant[1] countries experience slower development, due to several economic and political factors. One of the economic channels is the Dutch disease, which states that an increase in natural resources, rapid improvement in the extractive sector could affect the country's currency and it could deteriorate other sectors' competitiveness, which will crowd out the development

[1] For clarification, under natural resources, most of the authors mean non-renewable energy sources, more specifically oil and gas resources (Ross, 2015) (Badeeb et al., 2017).

in these non-resource related sectors (Sachs & Warner, 1995). Another economic channel is coming from the volatile oil price, which causes macroeconomic instability in resource-rich countries and deteriorates its economic development (van der Ploeg et al., 2010). Other channel is that the resource curse could deteriorate development through it causes less incentive to invest in human capital as discussed for example in Gylfason (2001). A large part of the theory measures the political factors behind the curse, the so-called political resource curse. As Ross (2015) summarized, the resource curse accelerates rent-seeking political behavior and that could hurt democratic development in a country. Also, resource abundance potentially increases corruption and deteriorates institutional setup which again harms the development (Ross 2015). Literature also focuses on the other direction of the institutional quality channel and suggests that the curse is not deterministic, and heterogeneity among resource-rich countries is large and mostly related to the initial institutional setting (Mahdavi, 2020a) (Ross, 2015).

2.2.2. Empirical Resource Curse Literature Review

Given the scope of my work and the size of the literature, I will just highlight some of the empirical findings in the resource curse literature. In general, the existing analyzes mostly focus on the oil-related resource curse, but the measurement of the abundance is varying between papers. Early stages of the research used exported resources, or the size of the mining sector, but today, the development of the data coverage creates space for more precise measurements: either by using quantity, oil production, value of the production and resource rent in a country, or one part of the papers utilize only the giant discoveries and measuring the effect of these resource shocks (Ross, 2015). Normalization of the resource metrics is also varying between studies, some measure per capita, per GDP, per export, or per total of government revenue resource abundance (Ross, 2015).

Economic channels related to Dutch disease and price volatility are quite accepted relations. For example, by using panel data around 85 countries Iimi (2007) proves that Dutch disease exists and affects economic development, although institutional factors could cause heterogeneity between countries. van der Ploeg and Poelhekke (2009) measure the oil price volatility effect and find the importance of this volatility channel. As an additional mechanism behind the resource curse Gylfason (2001) highlights, by using 85 country samples from 1965 till 1998, that education-related factors are also negatively affected by the resource abundance, the natural resource dependency potentially crowds out development in human capital. Similar connection between human development and resources was found by Gylfason and Zoega (2006).

Ross (2015) summarized that according to the empirical findings political resource curse exists and it is empirically well tested for three different effects. First one is the effect on democracy: Anderson and Ross (2014) use a panel dataset of 163 countries and find the political resource curse, countries with higher oil production experienced worse institutional and democratic setup. Tsui (2011) also finds that large resource (oil) discovery decreases the chance for democratization. Ramsay (2011) measures the increasing income on political institutions and finds a negative correlation in oil-producing countries. A few political resource curse papers focused specifically on the resource abundance (mainly oil) effects on political regimes. For example, Andersen and Aslaksen (2013) measure the resource curse's effect on political stability and find that in non-democratic countries resource abundance (oil specifically) expands the duration of the non-democratic leader. The second channel is between resource abundance and civil wars, according to these analyses there is an inverted U-shape relationship between increasing resource abundance (not just oil, but minerals as well) and the chance of civil war (Ross, 2015).

Third, and for my analysis an important causal mechanism is between institutional quality and the resource curse. Part of the papers focuses on how initial institutions affect the resource curse, while the other parts measure the relationship oppositely, if the resource curse deteriorates institutional quality (Ross, 2015). These conditional resource curse analyzes, like Mehlum et al. (2006) suggest that the initial institutional setting mainly determines if a country experiences a resource curse. Mehlum et al. (2006) uses a simple regression method with interaction in 87 countries and finds this conditional resource curse. On the other hand, researchers also suggest that the resource curse deteriorates the institutional quality and increases corruption as well (Ross, 2015). Arezki and Brückner (2011) claim by exploring 30 oil-exporting countries from 1992 – 2005 that corruption increases, and political rights decrease in case of increasing oil rent. According to Brollo et al. (2013) in Brazil oil-related transfers also increased corruption in that country.

According to my research, resource curse theory relies more on panel datasets, panel regression models (Papyrakis & Gerlagh, 2004) (Arezki & Brückner, 2011) (Gylfason, 2001). Recent analyzes which mostly capture oil shocks use different methods as well, for example, survival analysis (Andersen & Aslaksen, 2013) or instrumental variable method (Ramsay, 2015) (Mahdavi, 2020a).

Critiques of the resource curse theory have emerged during the years, some papers highlight the potential problems behind the resource curse empirical methodologies (Ross, 2015), for example, the exogeneity assumption behind resource discoveries (pre-resource curse: Cust – Mihalyi, 2017), or the reverse causality behind the institutional variables and the resource curse (Ross, 2015). But overall, the empirical analysis shows that resource abundance could be, but not always a curse: resource curse literature strongly claims that in a specific, mostly institutional setting resource curse could happen, and resource abundance could deteriorate the countries' development. When investigating this institutional setting, the literature focuses mostly on country-level institutional measures. However, the oil and gas-related industry is rather centralized, and it is mostly dominated by large National Oil Companies (Mahdavi, 2020a), so it is worth investigating this specific market actor's setup because this might be a cause behind the heterogenous resource curse effect.

2.2.3. The National Oil Companies

The National Oil Companies (thereafter NOCs) are dominating the oil sector, controlling around 90% of the global oil and gas reserves and 75% of the total production (Tordo, 2011 p.XI). According to Heller and Mihalyi (2019 p.20), several oil-producing countries are NOC dependent, in at least 25 countries the natural resource revenue from NOC was more than 20% of the government revenue in 2013. It is a consensus among researchers (Victor, 2013) and it is clear from the numbers above as well, that NOCs are key actors in oil production. Due to their dominance and the importance of the oil sector in general, several papers investigate the oil market evolution and the National Oil Companies performance, however only a few analyze the economic impact of these companies (Victor, 2013) (Heller & Mihalyi, 2019). Heller and Mihalyi (2019) suggest that the devoid of empirical papers incorporating NOCs' properties into the resource curse is due to the lack of adequate and global database about these companies. In the following short section, I will briefly summarize the main conclusions in the existing literature which investigates the properties of the NOCs and then I will focus on Mahdavi's (2020a) work as the author created an extensive dataset about the NOCs (Mahdavi, 2020b), which opens the space for a more detailed analysis of the NOCs' contribution to the resource or carbon curses.

Victor (2013 p.447-448) suggests that the large number of NOCs exist because of the weak public institutions, underdeveloped private sectors, also because governments wanted to control fiscal revenue and wanted to use oil export in their external affairs. Due to this large state control and lucrative revenue perspective, Riaño and Hodess (2008) claim that the extractive sector is one of the most vulnerable sectors for corruption and inefficiency. Therefore, it is not a surprising fact that resource curse literature finds that institutional factors and corruption are in connection with resource abundance. Some analyzes empirically claim NOCs inefficiency and non-transparent behavior: according to Eller et al. (2011) the dominance of national oil companies worsens the economic efficiency, NOCs are less efficient in generating oil revenues than the non-state-owned companies with similar parameters. Eller et al. (2011) used a company-level dataset and measured the revenue-making efficiency of 78 Oil Companies, using parametric and non-parametric panel models. Victor (2007) suggested a similar result. Conclusion from Heller and Mihalyi (2019) was also similar to the previous papers. They have created and used a database containing 75 NOC from 2011 – 2017, besides the fact that they also suggested NOCs are non-transparent and there is a large potential of inefficiency and/or rent-seeking behavior, a large part of their paper focused on the heterogeneity among NOCs. NOCs could be different in several dimensions, in their size, economic power, institutional power, type of resource, and these factors could determine if NOCs contribute to national wealth or deteriorate the home country from its potential development (Heller & Mihalyi, 2019).

Overall, the existing literature claims that NOCs, in general, are less efficient and transparent enterprises, thus this could be a potential factor behind the institutional-driven resource curse effect. However, as the authors highlight heterogeneity among NOCs is large, great example countries, like Norway, show that a country could avoid the NOC-driven resource curse. Therefore, it is important to measure not the NOCs' contribution in general but to capture the difference between NOCs' setups. By controlling for these differences, I could understand how heterogeneity among NOCs potentially contributes to the carbon curse. Given the fact that nearly all the resource-rich countries have National Oil Companies, it is important to measure the heterogeneity between NOCs even from a practical perspective, because it is not possible to create a valuable comparison group among resource-rich countries without NOC. Mahdavi's recent dataset (2020b) creates an opportunity to investigate these differences between NOCs, as the author highlighted in his recent paper (Mahdavi, 2020a).

According to the paper from Mahdavi (2020a), institutions behind the natural oil wealth are different and this institutional setting could largely explain the variation behind the resource curse effect. The author calls this phenomenon as the conditional resource curse. By examining 69 resource-rich countries and using a database that contains information about several attributes of the NOCs, Mahdavi (2020a) measures the conditional resource curse. Madhavi's (2020a) hypothesis was that regulatory NOCs will deteriorate transparency and cause higher bribery than NOCs without regulatory power. Regulatory power means that NOCs have power over the procurement process, contract awarding method (Mahdavi, 2020a p.14). This hypothesis is rooted in the agency theory and suggests that SOEs are less transparent, institutional oversight is weaker than in the case of ministries, or public entities. It is due to the asymmetric preferences of the public sector and private sector agents, which will cause moral hazard if there is no institutional structure or boundaries which support transparency and avoid deviation from social interest. Mahdavi (2020a) used the Bayesian approach and instrumental variable approach as well to measure the effect of the existence of regulatory NOCs on bribery and found positive relationships. He suggested that the resource curse is conditional on the NOC's institutional setup, which is an important new aspect for policymakers and academics.

Mahdavi (2020a) used other NOC attributes as control variables, for example, the economic power of the NOC. The author did not test explicitly the conditional resource curse on this variable, however, as it is suggested in Heller and Mihalyi (2019), other types of NOC attributes could also contribute to different results regarding the performance and the impact of the NOCs. NOCs with great economic power generate notable revenues for the countries (Victor, 2013), and in general rent-seeking behavior could be more problematic if there is a monopoly in the market, which is just more intense if a company is a state-owned enterprise (Coşar, et al.., 2019). Therefore, this NOCs attribute has great potential to deteriorate NOCs contribution to the economic development.

This summary suggests, I could not identify any papers which linked NOCs to environmental or climate outcomes, although the resource curse claims that the curse is not deterministic and one potential heterogeneity could come from the oil sector setting, more specifically could arise from the different National Oil Companies setup. Build on these findings, I will introduce my main theory, the carbon curse, and its extension with NOCs' setting.

3. The Carbon Curse

3.1. Theoretical Foundation of the Carbon Curse

The resource curse focuses on the institutional and economic dimensions of resource abundance but neglects its potential environmental effect. Literature on environmental degradation however mostly neglects the link between resources and pollution. Pathbreaking work by Friedrichs and Inderwildi (2013) linked the two issues and proposed that fuel-rich countries (measured by oil and coal endowments) face several counter incentives during their decarbonization effort.

Different than the CO2 emission analysis, where emission is measured as CO2 per capita, carbon curse literature uses CO2 emission per GDP (Friedrichs & Inderwildi, 2013). It is a more precise way to measure CO2 intensity in this context since it captures natural factors and production-related emissions, rather than the income-related per capita pollution (Neumayer, 2002) (Chiroleu – Assouline et al., 2020).

In the following part of this section, I will present the four potential channels which could cause higher carbon emission intensity in case of recourse abundance based on Friedrichs and Inderwildi (2013 p.1359-1363) and I also include some studies which discuss the importance of specific channels.

- **Extractive emission related pollution:**

The first channel suggests that fuel extraction and production is a highly polluting process, large energy inputs are needed to produce these fossil energies and the by-products of the production are also emitting (p.1359). This channel, that fuel industry a polluting one is independently discussed a supported by Masnadi et al. (2018).

- **Fuel-related crowding out in industrial structure and energy mix:**

According to the authors (Friedrichs & Inerwildi, 2013 p.1359-1360), two types of crowding out effect could result in a causal mechanism between fuel endowments and emission. First, the fossil fuel related extractive industry could crowd out other industrial developments, for example in the manufacturing industry. Authors suggest that this type of crowding out could cause slower economic development, which they claim would "suppress the rise of carbon intensity", therefore it creates a potential carbon curse weakening channel (Friederichs & Inderwildi, 2013 p.1359). The second crowding-out channel is more straightforward and related to energy usage and production. It claims that high fossil energy endowment could crowd out low-carbon energy from the countries' energy mix. This means that fossil fuel countries are not in a rush to invest in renewable energies.

According to my understanding, the first crowding-out effect is largely related to the resource curse, where other sectors develop slower due to an existing and large extractive sector. The second crowding out effect more relates to the political resource curse, because it highlights that the political motivation to be more environmentally friendly is weaker in resource-rich countries.

- **Fuel consumption subsidies**

The third mechanism behind the carbon curse is related to politics and institutional factors, therefore it strongly builds on the political resource curse literature. According to the descriptive examples presented in the paper, Friederichs and Inderwildi (2013) claim that resource-rich countries tend to subsidize fuel consumption more, which will cause inefficient and highly polluting energy consumption. In these countries resource-rich governments see subsidies as a potential loss, but not as a direct cost to the government, domestic pressure on politics to subsidize national resources is high and the large export revenue from fossil fuel easily offsets domestic subsidies (p.1362). This large existence of subsidies in the oil-related energy market in case of resource abundance was proved by Coady et al. (2015).

- Fewer incentives to invest in energy efficiency:

According to this channel (Friederichs & Inderwildi, 2013 p.1360-1361), resource-rich countries' incentive to produce and use their energy in an efficient way is less strong than for countries with scarce energy. Leaders in resource-rich countries could see potential in energy-intensive activities and sectors. Moreover, business actors could even face lower energy prices (as suggested in the previous channel), which could be a comparative advantage for energy-intensive industries.

Friederichs and Inderwindi (2013) support their carbon curse hypothesis by using descriptive analysis of 41 countries and find a promising correlation between the emission and resource dependence. However, they suggest that empirical analysis is needed to make sure that the carbon curse exists and there is a clear relationship between resource abundance and CO2 emission.

These channels suggest, the carbon curse theory builds on the resource curse (mostly on the political resource curse) and claims that government and other actors in the economy have an incentive to use resources inefficiently, and focus only on the existing polluting resource, which will result in larger emission.

3.2. Empirical Carbon Curse Literature Review

According to my research, only a few papers tested the carbon curse explicitly, but some CO2 emission analyzes also included fossil abundance in their models.

For example, Wang et al. (2019) measure the connection between carbon emission efficiency and resource abundance in China at the provincial level between 2003 and 2016. The authors find that increase in the resource dependence decreases energy efficiency (a 1% increase causes a 0.04% decrease in efficiency) and an increase in resource endowment decreases energy efficiency as well (Wang et al., 2019 p.209). This finding supports the existence of the fourth carbon curse channel suggested in Section 3.1. Wang et al. (2019) use Slacks – based Measure (SBM) to calculate energy emission efficiency and then a Tobit model to measure the relationship between energy efficiency and resource abundance and resource dependence.

Ike et al. (2020) measure the carbon curse effect in 15 oil-producing countries between 1980 – 2010. They do not explicitly focus on carbon curse theory, rather build their assumptions on Environmental Kuznets Curve (for example they measured emission and oil production in a per capita term). They used the Method of Moments Quantile regression with fixed effect to be able to capture the emission factors at a different pollution level. According to their findings, in the first six pollution quantiles, crude oil production significantly affects CO2 emission, but this significance disappears at the top four pollution quantiles. This means a carbon curse effect that fades away after a certain pollution level. Ike et al. (2019) explained this heterogeneity by the difference in the institutional setting, which could cause possible inverted U-shaped relationships. Besides the MMQR method this paper uses other panel regression approaches, for example fix effect model with Driscoll and Kraay standard error and given the fact that they use time-oriented databases, they also tested several time-series properties.

Neumayer’s (2002) early work also contributes to the carbon curse theory since it captured the potential environmental factors' effect on CO2 emission per capita. The author measures the effect in a large database, using 106 countries between 1960 and 1988. A positive relationship between fossil abundance and emission was found even after controlling for several types of resources and environmental factors (like weather variables) in the model. Neumayer (2002) used a simple OLS model with time control because using a fixed-effect model was not appropriate given the fact that there were no country-level within variations in his independent variables.

Balsalobre-Lorente et al. (2018) measure the natural resource abundance effect on emission per capita in five core EU countries between 1985 – 2015. Contrary to the carbon curse theory they find a negative connection between natural resource abundance and emission. They suggest that if one country is abundant in natural resources, it will import less energy, and given the fact that importing energy is heavily polluting, it will result in a lower CO2 emission. During their research, Balsalobre-Lorente et al. (2018) use the panel least square method after checking the necessarily time-series properties due to the low number of countries in their database. This analysis is important and warns that the relationship between emission and resource abundance is complex, although the precise interpretation of the result is challenging because the paper does not contain any information about what types of natural resource abundance measure the authors used.

On a somewhat larger database, Bekun et al. (2019) find different results than Balsalobre-Lorente et al. (2018). Bekun et al. (2019) investigate 15 EU countries from 1996 – 2014 to measure the effect of resource rent (as % of GDP), renewable, and non-renewable energy consumption on emission (measured by kg CO2 emission). According to the paper, there is a long-term positive relationship between resource rent and CO2 emission. Regarding the methodology, Bekun et al. (2019) use Pooled Mean Group Autoregressive Distributed Lag (PMG – ARDL) model and Granger causality, to deal with a database long in time, but narrow in cross-section.

After introducing studies with indirect carbon curse measurement, I end this section by presenting the paper which is a pioneer in measuring the direct carbon curse hypothesis. A recent paper from Chiroleu – Assouline et al. (2020) directly captures the carbon curse by using 29 developed countries from 1995 till 2009. They test the hypothesis at a country level and a sectoral level using a panel regression approach. According to their results, there is a U-shaped relationship, which does not support the carbon curse for countries with weak resource endowment, until a point relationship between resource abundance was negative. However, in the case of resource abundance countries, increasing resource endowment results in higher emission, therefore they suggest that the carbon curse exists, the effect is non-monotonous and probably more heterogeneous than Friedrichs and Inderwildi (2013) claimed. They also find that coal alone does not cause a carbon curse. After country level, they measure sectoral level carbon intensity and find that resource-rich countries are more polluting, not just in the energy-intensive sectors but also in the other sectors, which suggests spillover effect and provides evidence for the fourth carbon curse channel presented in Section 3.1.. Regarding their model and their methodology, Chiroleu – Assouline et al. (2020) use CO2 per GDP emission (PPP adjusted real USD) and measured the abundance by using the stock present value of the stream of expected rents in gas, oil, and coal (2005 USD). They use fixed-effect models with Driscoll-Kraay standard errors to correct for cross-country dependence (similar to the empirical research presented in Section 2.1.2.).

The carbon curse literature review suggests that the empirical analysis of this theory is rather scarce, the existing implicit carbon curse literature is mostly built on Environmental Kuznets Curve. Nearly all the papers found some positive relationship between resource abundance and emission, however, the metrics are different and the most relevant paper from Chiroleu – Assouline et al. (2020) showed that the relationship is probably more complex and heterogeneous than initially assumed. Building on the resource curse theory, heterogeneity could come from the institutional and economic setup in the oil market, so I will incorporate this channel into the carbon curse model.

3.2. The Carbon Curse and the NOCs

According to my literature review, there is no empirical analysis, which implemented NOC attributes to the carbon curse model and measured the conditional carbon curse effect. In my analysis, I distinguish between countries with NOCs, those with majority ownership in the sector, and whether the NOC has a regulatory role. In this section, I discuss the potential channels through which the role of a NOC may impact CO2 emissions.

As I suggested in Section 2.2.3. I will introduce two NOC settings. The majority of the NOC literature focuses on institution-related factors, Mahdavi (2020a) measures regulatory NOC channel with respect to the resource curse. However, as I mentioned earlier, Mahdavi (2020b) dataset also contains economic power measurement, if a country has NOC with above 50% producing power. NOC with strong economic power (thereafter monopolistic NOC) is a less discussed topic, but I believe large economic power in the hand of the state-related National Oil Companies could also act like large institutional power, therefore in the following, I will focus not just on the regulatory NOC effect, but also on this monopolistic NOC effect.

I believe there is a stronger counter incentive to invest in different energy sources (Section 3.1. second crowding out channel) in case of a strong NOC power, because it is the political elite's interest to keep this sector elevated due to its high rent-seeking potential. Since the government's part in the energy sector is stronger in case of a monopolistic NOC and the deviation from public interest could be more severe in the case of regulatory NOC, the political interest could prevail more. It could materialize in the fuel subsidies channel and in weak incentives to invest in energy efficiency channel (Section 3.1. third and fourth carbon curse channels). To summarize my assumptions which build on Mahdavi (2020a), the motivation to maintain a highly polluting oil and gas producing sector could be more severe if a NOC has relatively large economic or regulatory power.

To summarize, the carbon curse builds on the resource curse theory, mostly in terms of channels which relate to political incentives. The carbon curse theory suggests several resource-dependency factors that cause higher emission in oil and gas-rich countries. The literature review provides support for my claim that carbon curse is probably a more complex and non-deterministic phenomenon, and heterogeneity of the effect could be the result of different NOC settings. Build on these assumptions, in the following section, I will introduce my empirical model.

4. Empirical Strategy and the Model

In this section, I will introduce my estimation strategy. First, I will present the basic carbon curse models and their variables, then I will incorporate the National Oil Companies related metrics to that model. After introducing the equations, I will discuss the empirical methodology of my analysis.

Basic carbon curse models:

$$ln\left(\frac{CO2}{GDP}\right)_{i,t} = \beta_0 + \beta_1\left(\frac{resource\ prod}{GDP}\right)_{i,t} + \beta_2\left(\frac{resource\ prod}{GDP}\right)_{i,t}^2 + \beta_3' X_{i,t} + \alpha_i + \nu_t + \varepsilon_{i,t} \quad (1)$$

$$ln\left(\frac{CO2}{GDP}\right)_{i,t} = \beta_0 + \beta_1\left(\frac{resource\ prod}{GDP}\right)_{i,t} + \beta_2' X_{i,t} + \alpha_i + \nu_t + \varepsilon_{i,t} \quad (2)$$

Index *i* represents a country, while index *t* captures a year.

Regarding the dependent variable, similar to the original model (Friederichs – Interwildi, 2013) and Chiroleu – Assouline (2020) I will measure the CO2 intensity by CO2 per GDP in a given i country in a given t year to focus less on the income and EKC theory related factors, and more on the production-driven resource-related values. With respect to the key independent variable, the resource curse and carbon curse literature are diverse in the approach, how they measure the abundance variable. During my analysis, I will use oil and gas production value and measure it a per GDP metric (in PPP adjusted real values). I choose only oil- and gas-related production (and excluded coal) because the literature suggests that these are the most important resource curse factors (Chiroleu – Assouline, 2020), and because national oil companies are oil- and gas-related upstream (extracting and producing) companies. I choose the production variable over resource rent measures because it specifically captures the amount of resource the country utilizes each year, so I believe this is a close measure to the actual oil and gas dependence of the country. As for the conversion, I will use production value in a per GDP metric in order to capture the sector's importance in proportion to the economy. For a small economy, significantly less resource is sufficient for large dependency. Therefore, I will use per GDP metrics to understand the effect of resource dependency. I will measure the curse in a linear form (equation (2)), and I will test the quadratic form of the resource abundance as well (equation (1)), following the literature (Chiroleu – Assouline et al., 2020) which suggests that the effect might be non-linear. The individual effect of country i is represented by α_i , which contains country-specific factors such as cultural or structural country effects. Year errors ν_t capture potential structural changes worldwide in each year.

My control variables are based on Chiroleu – Assouline et al. (2020). These controls aim to identify other factors which could influence carbon intensity and are in a relationship with resource abundance and potentially could cause biased estimation in case of their omittance. The first of this control variable is population. It is well known from EKC literature that the population itself is a large contributor to the emission. Given the fact that in carbon curse literature the emission variable is in CO2 per GDP form, it is important to capture the missing population-related effect. For two countries which are similar in terms of GDP but different in terms of population, I expected different emission intensity, because a larger population requires more CO2-related energy demand. The second type of control variables are related to external weather factors. Similar to Neumayer (2002) I will include controls regarding the weather conditions in a country to measure potential CO2 intensity differences coming from the weather-related factors. The third group of variables is the human-related institutional factors, Chiroleu – Assouline et al. (2020, p.18) referred to them as "preferences and policy measures", indirect channels to the carbon curse effect. I am cautious with these variables (with renewable energy and environmental stringency variables specifically) to avoid that my controls are measuring my main direct effect or causing unequivocal interconnectedness in my model. For example, if I include renewable energy per total energy, I will cause clear interconnectedness between the oil and gas variable and renewable variable. Plus, I would also risk that this renewable variable which is affected by resource abundance and NOC setting indirectly measures the carbon curse or conditional carbon curse effects. Also, I would like to keep as large the database as it is possible, and not losing too many countries, and variables like renewable share or environmental stringency index are only available for a small and mainly developed country group. Due to these considerations, I will include two controls to capture the human-related factors. The first one is a standard country-level institutional setup, which I will measure by the policy index. The polity index, ranging from -10 (total autocracy) to 10 (total democracy) is a common measurement to institutional setup, and it controls for a basic level of responsible and non-rent seeking governance and transparency. As a second control, Chiroleu – Assouline et al. (2020) measured technological development, which I will capture by the per capita GDP, as a proxy for the technological level. Alternative technological level measurements, like the number of patents, are available only for the developed countries, therefore I choose this less precise measure to avoid a drastic cut in my database. Table 1. in Section 5 will contain summary statistics of these variables. Regarding the potential transformation of my variables, I will present pollution measure, per capita measure, and population measure in a natural logarithm. I keep abundance measures in a ratio form, both because resource dependency is a transformation itself and because my dataset contains non-resource-rich countries as controls.

Regarding my hypothesis, I would expect resource dependency will affect countries' emission intensity positively, β_1 is expected to be positive in both equations, although the quadratic term's coefficient (β_2) in equation (1) is expected to be negative – to get an inverted U-shape relationship. Chiroleu – Assouline et al. (2020) found a simple U-shape relationship, so that could be also a potential shape for the slope.

After I formatted my basic carbon curse model, I will present the conditional carbon curse models with respect to the different powers of NOCs in the (3)-(6) equations:

$$ln\left(\frac{CO2}{GDP}\right)_{i,t} = \beta_0 + \beta_1 \left(\frac{resource\ prod}{GDP}\right)_{i,t} + \beta_2\left[\left(\frac{resource\ prod}{GDP}\right)_{i,t} \times regulatoryNOC_{i,t}\right] + \beta_3 \left(\frac{resource\ prod}{GDP}\right)_{i,t}^2 + \beta_4[\left(\frac{resource\ prod}{GDP}\right)_{i,t}^2 \times regulatoryNOC_{i,t}] + \beta_5' X_{i,t} + \alpha_i + \nu_t + \varepsilon_{i,t} \quad (3)$$

$$ln\left(\frac{CO2}{GDP}\right)_{i,t} = \beta_0 + \beta_1 \left(\frac{resource\ prod}{GDP}\right)_{i,t} + \beta_2\left[\left(\frac{resource\ prod}{GDP}\right)_{i,t} \times regulatoryNOC_{i,t}\right] + \beta_3' X_{i,t} + \alpha_i + \nu_t + \varepsilon_{i,t} \quad (4)$$

$$ln\left(\frac{CO2}{GDP}\right)_{i,t} = \beta_0 + \beta_1 \left(\frac{resource\ prod}{GDP}\right)_{i,t} + \beta_2\left[\left(\frac{resource\ prod}{GDP}\right)_{i,t} \times monopolisticNOC_{i,t}\right] + \beta_3 \left(\frac{resource\ prod}{GDP}\right)_{i,t}^2 + \beta_4[\left(\frac{resource\ prod}{GDP}\right)_{i,t}^2 \times monopolisticNOC_{i,t}] + \beta_5' X_{i,t} + \alpha_i + \nu_t + \varepsilon_{i,t} \quad (5)$$

$$ln\left(\frac{CO2}{GDP}\right)_{i,t} = \beta_0 + \beta_1 \left(\frac{resource\ prod}{GDP}\right)_{i,t} + \beta_2\left[\left(\frac{resource\ prod}{GDP}\right)_{i,t} \times monopolisticNOC_{i,t}\right] + \beta_3' X_{i,t} + \alpha_i + \nu_t + \varepsilon_{i,t} \quad (6)$$

I will measure conditional carbon curses by adding interaction terms to the resource abundance variables. Economic power is measured by a monopolistic NOC dummy variable, institutional power is measured by a regulatory dummy variable (see the exact definitions of the variables in Section 5.1.). Since my theoretical framework suggests that heterogeneity in NOCs only matters if there are oil and gas resources in a country, I will measure the interaction terms without including monopolistic and regulatory dummies' non-interacting terms. As a robustness check, I will also calculate interaction terms by including base NOCs' variables, which will be presented at the end of Section 6.

Regarding the methodology, I will do panel data regressions. Among panel models, most of the economic literature utilizes the fixed-effect method. This method is also called within estimation, and it controls for country-level constant unobserved effects, and its identification is coming from the within-country heterogeneity (Wooldridge, 2012). The two-way fixed-effect model is a widely used method as well because it is not just controlling for unobserved, though within constant factors, but also for cross-country constant time effects. Given my macro-panel dataset and shocks which probably happened in the past, it is important to control for both factors, so I will use two-way fixed-effect models.

However, I should not take the fixed effect model for granted, because if a different method, namely the random effect model is applicable, it provides more efficient estimation than the fixed effect method (Wooldridge, 2012). The random effect model assumes that model variables do not correlate with the country-specific error term (Wooldridge, 2012 p.492). If this is true, I should use this method due to its lower standard error. I will use the Hausmann-test to check if my fixed-effect method is appropriate to this database. If the fixed-effect model is the more appropriate method (which I assume, because of the macro panel dataset), I should also test whether within section (in my model within countries) variations exist, because it is necessary for the identification. When using panel data, it is important to cluster the error terms to get standard error which corrects for autocorrelation and heteroscedasticity. Also, as the EKC and the carbon curse literature suggests, it is important to check potential correlation between the countries, if there is a cross-sectional dependence in the model, which would cause inefficiency (Hoechle, 2007). Therefore, as the last step, I will use Pesaran's cross-sectional test (Pesaran, 2021) and will correct my model by using nonparametric Driscoll-Kraay covariance estimation (Driscoll & Kraay, 1998) (Hoechle, 2007) to get a robust standard error if cross-sectional dependency exists. Besides the basic models, I will do robustness checks by using different time intervals, modified model specifications, and narrowed country groups.

As the last step in this section, I would like to discuss two potential problems, which could arise when using the above methodology and in general when measuring macroeconomic effects in a panel dataset. These issues are not always treated in the literature (both problems have been neglected in my main reference paper, Chiroleu – Assouline et al. (2020)). The first one is multicollinearity. A high but not perfect correlation between independent variables does not violate any model assumption, therefore the estimation is unbiased, but could increase coefficients' variance (Wooldridge, 2012). A large part of the carbon curse related papers and the CO2 literature neglect this potential problem, so due to these references, I will not consider it in my thesis explicitly, but as I suggested above, I was cautious in choosing my explanatory variables and tried to avoid inevitable correlation with my key independent resource intensity variable. The second issue could arise from stationarity. The time-oriented papers in the literature with analyzing only a few countries investigate stationarity properties and even some of the analyzes with panel datasets, like Liu et al. (2019) consider this issue. However, Chiroleu-Assouline et al. (2020) or Neumayer (2002) neglected this potential problem in their paper, and Wooldridge (2002, p.175) also suggests that if N (country) is large relative to T (year) in panel regressions the model assumptions are met. Thus, I will not test this issue in my main analysis with the large country group, but when I run robustness checks on a smaller, resource-rich country subsample (with 24 countries), due to the smaller number of country groups I will test this assumption.

5. Dataset Overview

5.1. Datasets

To measure the carbon curse and the conditional carbon curse concerning the power of the NOCs, it is crucial to construct a panel dataset that is wide in time and cross-country. As for the resource metrics, I used Ross and Mahdavi (2014), which provide information about the oil and gas production from 1932 – 2014. It contains information about countries' oil and gas production quantities (oil in barrel, gas in barrel of oil equivalent) and values (by using historical oil and gas prices). Regarding the carbon emission variables, I used data from the Global Carbon Project (Friedlingstein et al., 2020), which measures anthropogenic territorial-based CO2 emission (in millions of tonnes of CO2 per year). The third key dataset for my research is a database from Mahdavi (2020). This new dataset is not open and was provided for this thesis by the author. Panel data contains information about 175 countries' upstream (extracting and producing) National Oil Companies between 1905 – 2015. Among others following information available from the panel dataset[2]:

- whether a country has a national oil company at a given year,

- if this NOC is a major producer: NOC produce more than 50% of the country's total oil and gas production

- if the NOC has regulatory power: NOC has oversight or regulatory power over other oil companies in the sector

Other control variables were used from several sources: PPP adjusted real GDP measure from Penn World Table (Feenstra et al., 2015), institutional polity variable from the PolityProject

[2] All the variables are measured by dummy variables.

(Marshall – Gurr, 2018), environmental temperature measures from the Kaspacz dataset (Kapsarc, n.d.), and population measure from the UN population estimates (Unites Nations, 2019). Environmental measures cooling degree days (CDD) and heating degree days (HDD) measure “the heating and cooling needed to neutralize the deviation of surface temperature from a standard comfort level” (Chiroleu – Assouline et al., 2020 p.9). Therefore, if CDD (HDD) is high it means the temperature is higher (lower) than the reference, more cooling (heating) degree days are needed to compensate.

Overall, the final database is from 1980 – 2013, the panel database is unbalanced since post-soviet countries joined separately from 1991. The appendix will contain a robustness check with calculations only from 1993 – 2014. Due to some missing values in my controls, the final database contains 131 countries after 1993 and 110 countries before 1991 (two countries entered not in 1991, but in 1993). A summary of the variables could be found in Table 1 below:

Variables	Obs	Mean	Std. Dev.	Min	Max	Note	Source
Emission intensity	4,331	0.324	0.316	0.002	3.46	kg CO2 / real PPP adjusted GDP in 2017 USD	Friedlingstein et al.(2020); Feenstra et al.(2015)
Resource dependency	4,331	0.05	0.12	0.00	1.80	oil and gas production value / PPP adjusted real GDP in 2017 prices	Ross – Mahdavi (2015); Feenstra et al.(2015)
Regulatory NOC	4,331	0.23	0.42	0.00	1.00	Dummy. 1: country has regulatory NOC. 0: no regulatory NOC.	Mahdavi (2020b)
Monopolistic NOC	4,331	0.20	0.40	0.00	1.00	Dummy. 1: country has monopolistic NOC. 0: no monopolistic NOC.	Mahdavi (2020b)
Population	4,331	43811	146022	250	1399454	thousands of people	Unites Nations (2019)
Polity index	4,316	2.30	7.01	-10.00	10.00	from -10 (strongly autocratic) to 10 (strongly democratic), interregnum periods with missing values were coded as a simple transition between pre- and post-numbers	Marshall – Gurr (2018)
Per capita GDP	4,331	12794.78	18023.74	243.69	316664.40	PPP adjusted real GDP per capita	Feenstra et al. (2015); United Nations (2019)
CDD	4,200	5965.60	4503.57	3.40	16472.91	Heating degree days, Reference = 18 Celsius degree, frequency = 6hours	Kapsarc (n.d.)
HDD	4,200	6387.53	7208.96	0.00	33544.57	Cooling degree days, Reference = 18 Celsius degree, frequency = 6hours	Kapsarc (n.d.)

Table 1 Explanatory variables – summary statistics, details, and sources. Own table.

5.2. Descriptive Statistics

I will briefly highlight the descriptive part of my analysis relating to the carbon curse and the conditional carbon curse. Figure 1. presents the CO_2 intensity in 2000 by countries.

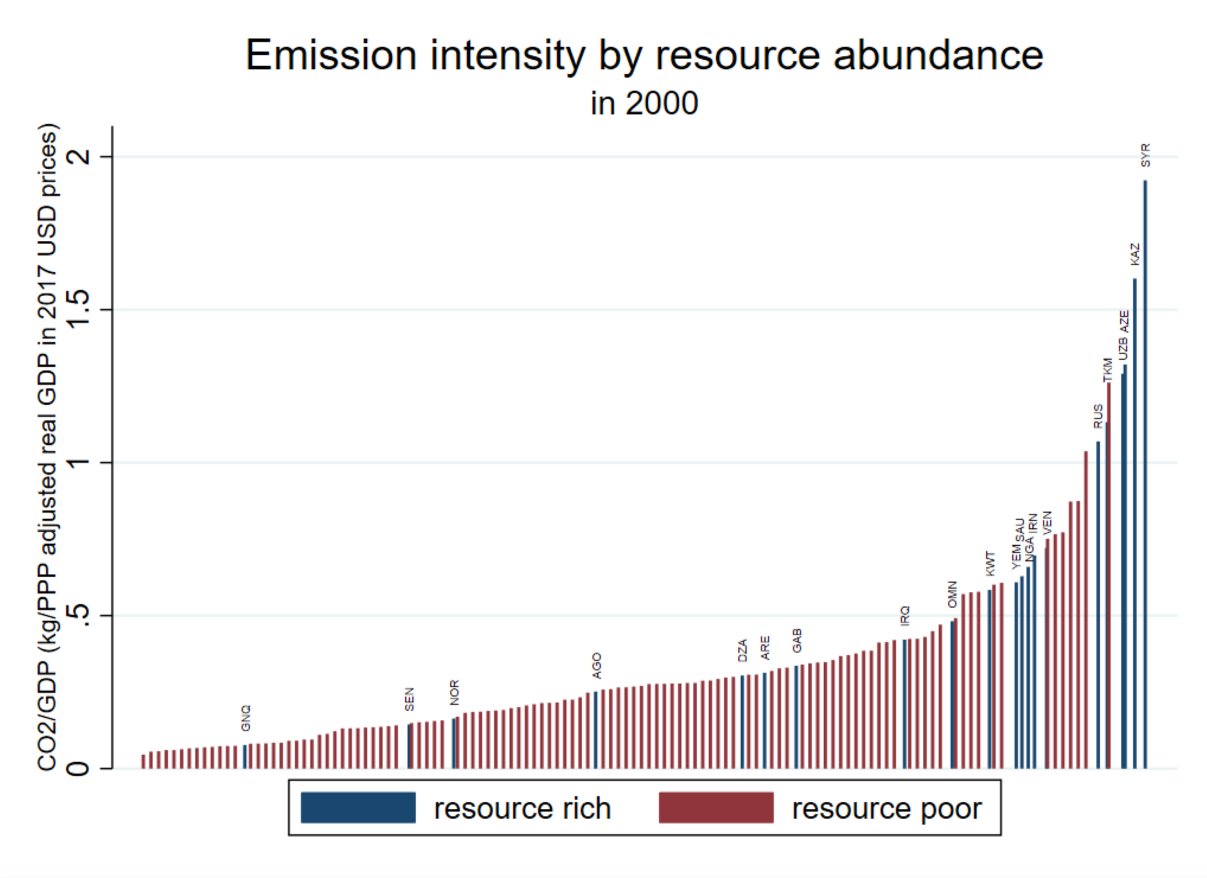

Figure 1. Emission intensity by resource abundance in 2000. Own figure. Sources: Ross and Mahdavi (2015), Friedlingstein et al. (2020), Feenstra et al. (2015). Note. Resource rich countries are the countries with > 10% of GDP large oil and gas production

Figure 1. highlights the importance of the carbon curse question. According to the table, oil- and gas-rich countries are the most emission intense nations. This result is in line with the previous findings of the literature.

But it might be just a yearly phenomenon, so I will present it in Figure 2. the historical evolution of the resource-rich and the resource-poor countries' emission.

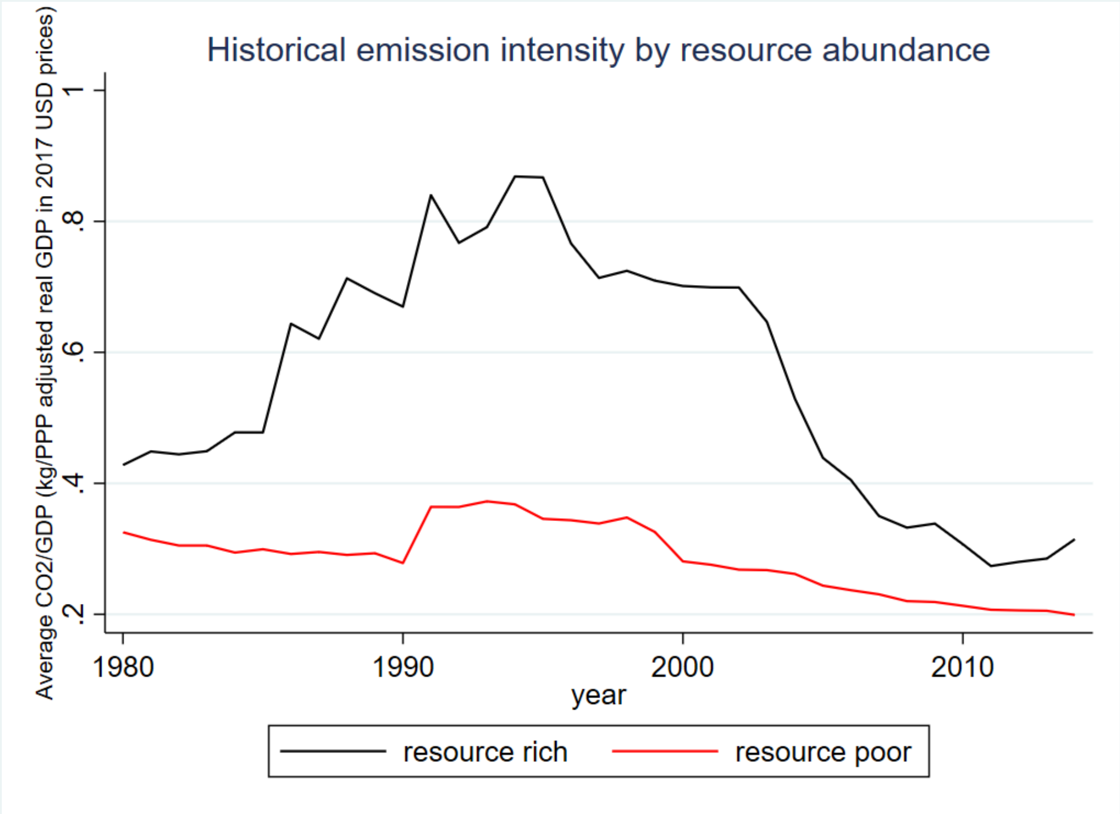

Figure 2 Average historical emission intensity by resource abundance. Own figure. Sources: Ross and Mahdavi (2015), Friedlingstein et al. (2020), Feenstra et al. (2015). Note. Resource rich countries are countries with > 10% of GDP large oil and gas production

The descriptive statistics for the carbon curse suggest that the difference between the two groups is visible, resource-rich countries have higher emission intensity than resource-poor countries. The difference is significant according to the simple T-test as well (Table 6 of the Appendix). On average over the time horizon, resource-rich countries' CO_2 intensity is 0.53 kg per PPP adjusted real GDP, while resource-poor countries' value is 0.29 kg per PPP adjusted GDP. Although Chiroleu – Assouline et al. (2020, p.14) measured CO_2 emission in simple kg metrics, which did not incorporate the different size of the nations, they found overall similar results, the emission is larger during the sample for resource-rich countries (although for them the difference is widening). However, this pure correlation does not mean any causal relationship, it just supports the claim of the hypothesis.

After the descriptive part of the simple carbon curse, I will discuss some statistics of the conditional carbon curse. First, I will present the historical chart of the CO_2 intensity per GDP for monopolistic NOC and regulatory NOC.

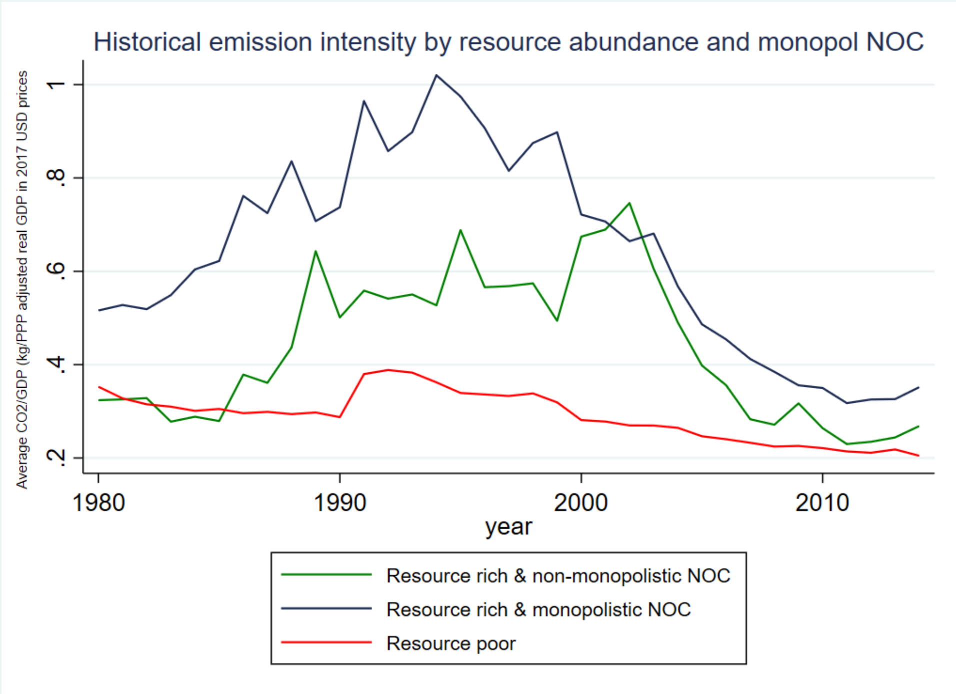

Figure 3 Average historical emission intensity by resource abundance and monop.NOC. Own figure. Sources: Ross and Mahdavi(2015), Friedlingstein et al.(2020), Feenstra et al.(2015), Mahdavi(2020). Note. Res. rich countries are with > 10% of GDP oil and gas prod.

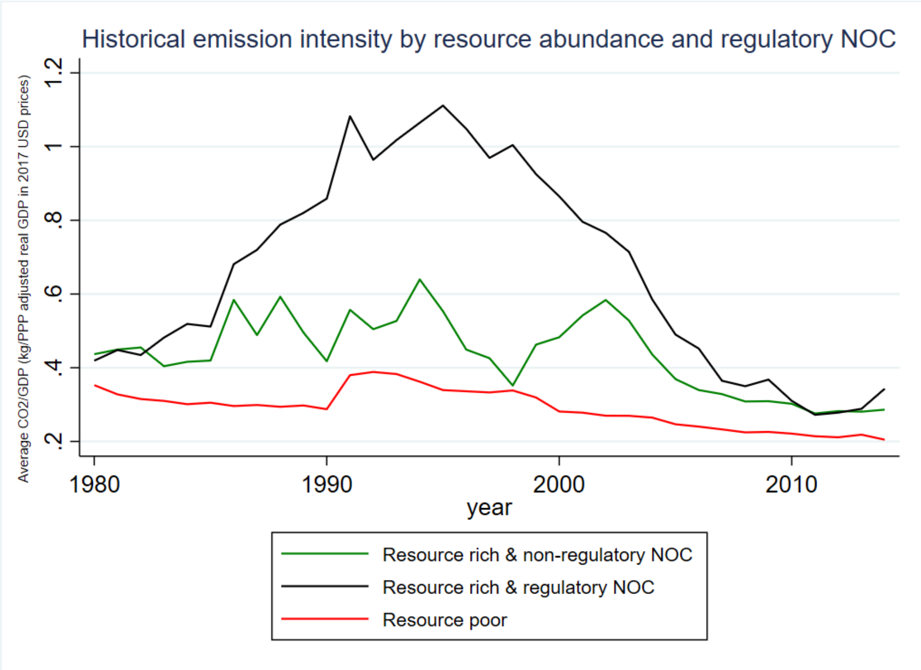

Figure 4 Average historical emission intensity by resource abundance and regulatory NOC. Own figure. Sources: Ross and Mahdavi(2015), Friedlingstein et al.(2020), Feenstra et al.(2015), Mahdavi(2020). Note. Res. rich countries are with > 10% of GDP oil and gas prod.

Both charts support that potentially, resource-rich countries with stronger NOC power experience a more severe carbon curse, although the differences seem to change over time and these charts only represent simple averages without controlling for any other factors.

Regarding the characteristics of the NOCs, I check if NOCs are as dominating as it was suggested in the literature. The answer is yes, the National Oil Companies highly dominate my sample, there are only 8 significant resource-producing countries in the whole period where is more than 1 year without NOC. Other resource-rich countries have NOCs. For example, in 2010, only two resource-rich countries have not had National Oil Companies. Therefore, as I suggested in Section 2.2.3, this dominance means it is not possible to check the NOCs' effect in general, because there is no valid control group among resource-rich countries, but without NOCs. However, as the literature suggests in Section 2.2.3. more detailed NOC controls are more appropriate, since there is a large heterogeneity within NOCs, so my main variables of interest are relating to NOC attributes.

In contrary to the existence of the NOCs, regulatory and monopolistic NOC characteristics are much more heterogeneous in the sample. In the resource-rich countries, there are in total 375 observations with regulatory NOC and 282 without regulatory NOC. While there are 379 observations with monopolistic NOC and 278 without them. Of these, 179 observations are only monopolistic but not regulatory NOC and 175 vice versa. According to these differences, these variables are suitable to measure different NOC characteristics.

Given the fact that emission-related differences (first channel in Section 3.1.) could be an easy explanation behind the different NOC patterns, thus I tested if regulatory and non-regulatory NOCs and monopolistic and non-monopolistic NOCs are similar in terms of oil and gas dependency. As it could be found in Table 7 and 8 of the Appendix, by using simple T-test I suggest, that groups are similar in terms of the oil and gas dependency.

As a last point of the descriptive analysis, I check the variance of the variables. In the case of a fixed-effect model, it is important to be able to identify within-country variances of the variables. Table 9 of the Appendix contains information about the results. It is visible that between variances exist, although a significant part of the overall variance will disappear as between variances are also high. In regulatory and monopolistic NOC, within variance exists, 22 countries experienced to change to regulatory or to the non-regulatory institutional setting during the sample, while 19 countries changed from non-monopolistic to monopolistic or vice versa. In addition, given the interaction method I use, I could measure not just the change in the regulatory or monopolistic power, but also the effect in case of resource dependency jumps in different NOC settings.

6. Results

Before I present the results of the final regression, I test the necessary properties of the model. First, I ran the Hausmann test[3], which revealed the expected result, that a significant difference between RE and FE exists, as the P-value is less than 0.05. Thus, I could reject the null hypothesis which assumes that models are the same. Therefore, the random effect model is not applicable, using the fixed-effect model proves to be a more adequate method.

	df	chi2(df)	Prob>chi2
Quadratic model (equation (1))	7	268.51	0.000
Linear model (equation (2))	6	286.82	0.000

Table 2. Hausmann test. Own calculation

Secondly, I tested my model for cross-sectional independence, by using the Pesaran's test, implemented in STATA. I found that cross-sectional dependencies exist at the 5% significance level, therefore I will present my fixed effect regression using Driscoll-Kraay standard error estimation. This non-parametric method corrects for autocorrelation, heteroscedasticity, and cross-sectional dependence, so it is a better option than using clustered robust error by countries.

Pesaran's test of cross-sectional independence	*coeff.*	*Pr.*
Quadratic model (equation (1))	-2.315	0.0206
Linear model (equation (2))	-2.425	0.0153

Table 3 Pesaran's test for cross-sectional dependence. Own calculation

After checking for the necessary pre-conditions, I present my regression results for the carbon curse model in Table 4.

[3] Due to the fact, that I included time dummies in my models, I corrected the Hausmann test degree of freedom, because these year dummies are time-invariant and would slightly mislead the test. This adjustment however does not change much regarding the test results, chi square values are high and as it was expected, the random effect model is not appropriate for my country panel.

	(1)	(2)	(3)	(4)
	FE	FE - Driscoll-Kraay	FE	FE - Driscoll-Kraay
	with quadratic term	with quadratic term	without quadratic term	without quadratic term
Oil&gas prod per GDP	1.364***	1.364***	0.749***	0.749***
	(0)	(0.000151)	(0)	(0.000151)
Oil&gas prod per GDP square	-0.550***	-0.550***		
	(2.94e-08)	(0.00164)		
ln per capita GDP	-0.347***	-0.347***	-0.341***	-0.341***
	(0)	(2.01e-08)	(0)	(3.77e-08)
ln population	0.651***	0.651***	0.678***	0.678***
	(0)	(1.05e-10)	(0)	(0)
CDD	2.02e-05	2.02e-05**	2.34e-05	2.34e-05**
	(0.155)	(0.0463)	(0.100)	(0.0224)
HDD	3.87e-05***	3.87e-05***	3.86e-05***	3.86e-05***
	(2.18e-07)	(2.76e-05)	(2.53e-07)	(1.97e-05)
Polity index	-4.736***	-4.736***	-5.033***	-5.033***
	(0)	(2.20e-05)	(0)	(1.12e-05)
Constant	4,186	4,186	4,186	4,186
R-squared	0.393		0.388	
Number of countries	131	131	131	131
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
pval in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Table 4 The Carbon Curse models. Own calculation

With respect to the resource dependency indicators, these results support my hypothesis, that an increase in resource dependence results in larger emission intensity. Regarding the shape of the relationship, the quadratic term is significant, the peak is in the independent variable's range [4], although the turn is after a high resource dependency level. Due to this reason, I consider that

[4] To calculate the turning point of the slope, I took the first derivative and equaled it to zero to get the dependency ratio after which the relationship was negative. According to my calculations it is 1.24, which means that oil- and gas-production value is 125% of the GDP. It means that the turning point is extremely large, but falls within the range of the oil and gas dependency ratio (max = 1.8).

the models (1)-(2) with quadratic terms are the more appropriate specifications. Due to the cross-country dependence that I estimated before, the fixed-effect model with Driscoll-Kraay error estimation in the model (2) is the best possible specification. According to that model, the carbon curse effect is different with respect to the resource dependency level. For example, if the resource dependency ratio increases by 0.01 from 0.15 to 0.16 (1 percentage point increase in oil and gas production to GDP), it will cause an increase in carbon intensity by 1.19% on average, if other variables are held constant. This effect is smaller if there is a one percentage point increase from 0.30 to 0.31, at this level, the effect is a 1.03% increase in emission intensity. My result suggests that the carbon curse exists, and the slope is an inverted U-shape. This slope is different from what was found by Chiroleu – Assouline et al. (2020), they suggested a U shape relationship. I believe that this difference could come from the fact that Chiroleu – Assouline et al. (2020) only measured the effect in developed countries, where development and institutional factors could mitigate the carbon curse effect if the resource dependency is small. Also, they used more detailed institutional controls, which could help the authors to capture indirect effects which could mitigate the carbon curse if the resource dependency is high.

Regarding the control variables, according to my result – coming from the model (2) – a 1% increase in population will result in a 0.651% increase in CO_2 intensity, which is logical because larger energy demand is needed in the case of a larger populations. Both HDD and CDD weather conditions have a significant effect on emission intensity. One unit increase in heating days (more heating days are needed to achieve reference temperature) leads to higher CO_2 intensity, which means that below-average temperatures increase CO_2 intensity. If more cooling days are needed (an increase in CDD) it also increases emission intensity. These results suggest that mitigating weather conditions both cause more CO_2 intensity. Human-related factors also suggest a significant relationship, a 1% increase in development (measured in per capita terms) increases the CO_2 intensity by 0.347% percentage. Since I include this proxy as a technological measurement, I find the relationship consistent with the literature, if a country is more developed and therefore has better technology the CO_2 intensity decreases. Regarding the institutional measure, I find that a more democratic institutional setting moderates emission intensity, and the effect is large, which is again, in line with the theoretical assumptions.

After I ran the carbon curse model and supported the theory, I test the conditional carbon curse (equation (3)-(6)) by including the regulatory and the monopolistic NOC characteristics in the models. I ran the Hausman and the Pesaran tests for these specifications, which are presented in Table 10 and Table 11 of the Appendix. The tests suggest that the fixed-effect model with Driscoll-Kraay error estimation is the most appropriate model-setting. I will present my results in the Table 5.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE - Driscoll-Kraay	FE	FE - Driscoll-Kraay	FE	FE - Driscoll-Kraay	FE	FE - Driscoll-Kraay
Oil&gas prod per GDP	0.571***	0.571	0.214**	0.214	1.863***	1.863***	0.901***	0.901***
	(0.00864)	(0.181)	(0.0492)	(0.242)	(0)	(5.94e-05)	(0)	(0.000235)
Oil&gas prod per GDP * Regulatory NOC	1.519***	1.519***	0.745***	0.745***				
	(0)	(0.00425)	(1.48e-09)	(0.00126)				
Oil&gas prod per GDP * Monopolistic NOC					-0.109	-0.109	-0.494***	-0.494*
					(0.641)	(0.769)	(4.87e-05)	(0.0751)
Oil&gas prod per GDP square	-0.315	-0.315			-0.736***	-0.736***		
	(0.289)	(0.455)			(0)	(0.000883)		
Oil&gas prod per GDP square * Regulatory NOC	-0.608**	-0.608						
	(0.0425)	(0.180)						
Oil&gas prod per GDP square * Monopolistic NOC					-1.135***	-1.135***		
					(0.000128)	(0.00128)		
ln per capita GDP	-0.350***	-0.350***	-0.338***	-0.338***	-0.348***	-0.348***	-0.344***	-0.344***
	(0)	(4.98e-08)	(0)	(4.23e-08)	(0)	(2.40e-08)	(0)	(1.69e-08)
ln population	0.634***	0.634***	0.673***	0.673***	0.610***	0.610***	0.665***	0.665***
	(0)	(3.15e-10)	(0)	(8.13e-11)	(0)	(2.77e-10)	(0)	(6.64e-11)
CDD	2.07e-05	2.07e-05**	2.51e-05*	2.51e-05**	1.82e-05	1.82e-05*	2.24e-05	2.24e-05**
	(0.140)	(0.0340)	(0.0764)	(0.0135)	(0.196)	(0.0899)	(0.114)	(0.0387)
HDD	3.86e-05***	3.86e-05***	3.87e-05***	3.87e-05***	3.94e-05***	3.94e-05***	3.87e-05***	3.87e-05***
	(1.78e-07)	(5.54e-05)	(2.19e-07)	(2.46e-05)	(1.12e-07)	(3.01e-05)	(2.24e-07)	(2.17e-05)
Polity index	-0.00489***	-0.00489***	-0.00557***	-0.00557***	-0.00516***	-0.00516***	-0.00600***	-0.00600***
	(8.67e-05)	(0.00903)	(8.89e-06)	(0.00313)	(3.67e-05)	(0.00367)	(1.73e-06)	(0.00117)
Constant	-4.548***	-4.548***	-4.999***	-4.999***	-4.340***	-4.340***	-4.856***	-4.856***
	(0)	(6.03e-05)	(0)	(1.48e-05)	(0)	(5.18e-05)	(0)	(1.44e-05)
Observations	4,186	4,186	4,186	4,186	4,186	4,186	4,186	4,186
R-squared	0.405		0.394		0.401		0.391	
Number of countries	131	131	131	131	131	131	131	131
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
pval in parentheses	*** p<0.01, ** p<0.05, * p<0.1							

Table 5 The Conditional Carbon Curse models. Own Calculation.

Due to cross-sectional dependence and to estimate my results with proper standard errors, I use the fixed-effect models with Driscoll-Kraay estimation, so model (2)-(4)-(6)-(8) are the appropriate results to look out for. As for the shape of the curve, the picture is more complex than in the case of the basic carbon curse, but overall, according to my findings, the existence of the conditional carbon curse for the institutional NOC setup is significant at every significance level. However, the presence of the conditional carbon curse in the case of monopolistic NOCs is insignificant (model (6)) or merely weakly significant (model (8)), when interacting with the linear resource dependency term. Moreover, model (6) provides somewhat contradictory results in the case of the quadratic interaction.

First, I will interpret the regulatory NOC results: model (2) and model (4) both suggest that the carbon curse is only significant in the case of the regulatory NOC interaction, and the non-interacting carbon curse effect is insignificant when using Driscoll-Kraay fixed-effect estimation. This means that if everything else is held constant, then on average an increase in the oil dependency ratio significantly affects CO2 intensity only in the case regulatory NOCs are existing in a country, therefore, I could accept my hypothesis about the conditional carbon curse regarding regulatory NOCs. As for the shape of the slope, quadratic terms are not significant in model (2). Since the quadratic terms became non-significant after Driscoll-Kraay estimation and the point estimation is quite distinct from the linear model, I prefer the linear model (model (4)) in this conditional carbon curse setup. The size of the carbon curse effect is quite similar in scale to the original linear carbon curse model (Table 4, model (4)), a 1 percentage point increase in resource dependence (a 0.01 unit increase in oil and gas production to GDP ratio) is expected to result, on average, in a 0.745% increase in CO2 intensity in regulatory NOC countries. Coefficients of population, weather conditions, and technological effects are similar to the simple carbon curse model, but the institutional setting variable's coefficient notably decreases, which supports the claim that institutional NOC heterogeneity was partially captured before in the country-level institutional setup. Overall, the non-significant quadratic term makes it more difficult to interpret the exact size of the effect, but my results support the conditional carbon curse hypothesis in terms of regulatory power.

For the monopolistic NOC carbon curse, linear interaction terms are not significant at the common 1% or 5% significance levels (model (6), model (8)). Due to the fact that the squared oil and gas dependence effects are significant in this model setting, I prefer the model (6) over the model (8). In this specification, monopolistic NOC is insignificant with the linear resource dependency interaction but significantly contributes to the decreasing shape of the dependence's effect. However, given its insignificant linear effect and because the non-conditional carbon effect's coefficient did not lose its significance, I would not draw a strong conclusion from this specification. One potential problem with this conditional carbon curse setup could be that the dummy variable might be a too simplistic metric to capture the economic power of the NOCs, thus, more precise metrics are needed to validate my hypothesis.

As the last step in my econometric analysis, to support my results, I run robustness checks: decreasing the time horizon of my model (calculating models from 1993 till 2013), running regressions with base NOC effects, and checking the conditional and simple carbon curses in stable resource-rich countries. First, I will discuss my result regarding this narrowed time frame: according to my findings, which can be found in Table 12 of the Appendix, the simple carbon curse results are very similar to my main findings presented in Table 5. As for the conditional carbon curse, none of the monopolistic NOC coefficients are significant, which supports the claim that I could not accept the conditional carbon curse hypothesis for this NOC attribute. The conditional carbon curse for regulatory NOC proved to exist, and its quadratic interaction term is significant as well, thus regarding this sample period, the carbon curse's shape shows an inverted U. Just for the comparison, linear model (Table 12 model (4) Appendix), which proves the existence of the conditional carbon curse for regulatory NOC, also suggests that the carbon curse only exists for the regulatory NOCs and on the non-regulatory subsample, the simple resource dependency effect is even negative. However, given the significance of the quadratic term, I suggest the quadratic model (Table 12 of the Appendix, model (3)) is a more precise specification for this sample, and in this specification the simple linear oil and gas dependency effect is not significant, at the usual 1% or 5% levels.

As a second robustness check, I include base interaction for regulatory and monopolistic NOCs, results are presented in Table 13 of the Appendix. The monopolistic NOC coefficients follow a similar insignificant pattern, seen in Table 5, where the basic monopolistic coefficient itself is insignificant. As for the regulatory NOC power, in the linear model, the base regulatory dummy is insignificant at the 5% significance level, while the interaction term remains significant and similar to the previous value. This supports the initial model setting, which I presented in Section 4.. In case of the quadratic model, the regulatory base effect is significant, but its effect is small, compared to the interaction term, so the conditional carbon curse remains significant and positively affects emission intensity if regulatory NOC exists. Quadratic interaction is significant in this specification, thus according to this model setting, the conditional carbon curse effect's outline is an inverted U-shape, although the effect is positive on emission until a high carbon intensity level[5].

As a final robustness check, I will narrow the sample to the stable resource-dependent countries of which 16 have regulatory NOC and 8 do not have non-regulatory NOC (N = 24), and measure the carbon and conditional carbon curses on this sample. I define a country as being stable resource-dependent if it produces oil and gas during the whole period at a minimum of 1% of the GDP. As I suggested in Section 3.2., due to the low number of countries in this sample, I

[5] To calculate the turning point of the slope, I take the first derivative and equal it to zero to get the dependency ratio after which the relationship is negative. According to my calculation, the peak of the conditional carbon curse is at 0.88, which means that the peak is after an existing, but high oil and gas dependency.

test these models for stationarity assumptions: for this, I use the unit root test, more specifically the second-generation Pesaran's unit root test (Table 14 of the Appendix). The test suggests that GDP per capita and resource dependency ratio and polity ratio are non-stationer at the first degree. To handle the non-stationarity, I take the first difference of these variables, which successfully handles the non-stationary issue. After I solved the non-stationarity problem, I run the Hausmann tests (Table 15 of the Appendix), which suggest that fixed-effect models are more appropriate than random effect model, so I ran two-way fixed-effect regressions with Driscoll-Kraay estimation (Pesaran's cross-country dependence tests are significant at 5% for every model specification, results are presented in Table 16 of the Appendix). According to my findings (Table 17 of the Appendix), the carbon curse only exists at a weak significance level (10% of significance) and I am not able to capture the conditional carbon curses on this sample. This could be the consequence of the lower variance in this resource-rich sample, and in general, the smaller sample probably does not represent the whole country pattern.

Although I believe the larger sample and my findings (presented in Table 4 and Table 5) provide evidence supporting the assumption of the carbon curse and the institutional conditional carbon curse hypotheses, however, the last robustness exercise highlights the point which I have suggested before: the carbon curse and the conditional carbon curse for regulatory NOCs are both significant in my main models, but results might be sensitive to the exact specification due to the macroeconomic context and country panel settings. Last but not least, the first two robustness checks pointed out, that the exact shape of the curse could be also sensitive in the case of the conditional carbon curse but both specifications supported the acceptance of the carbon curse and the regulatory conditional carbon curse hypotheses.

7. Conclusion

In this thesis, I estimated the countries' resource dependency effect on CO2 intensity and measured the heterogeneity of this effect for national oil companies' institutional and economic power. I used two-way fixed-effect models and estimated the standard error with Driscoll-Kraay estimation due to the existence of the cross-sectional dependence in my models. I included human- and weather-related controls and measured the potential curse with linear and quadratic resource abundance forms. Regarding the simple carbon curse, I found an inverted U-shape relationship, stronger reliance on oil and gas causes larger CO2 emission intensity, although the effect is decreasing (but positive till a high resource dependency level). However, the carbon curse effect seems to be significant only for countries with National Oil Companies that have strong institutional power, and I found simple linear relationship being a more appropriate specification for this setup[6]. I suggest that in a country with a regulatory NOC if there is a 1 percentage point increase in the resource dependency ratio, it will cause 0.745% higher emission intensity on average. Regarding the carbon curse for monopolistic NOCs, I was not able to prove the existence of the conditional curse.

Although I accept my carbon curse and conditional carbon curse hypotheses for regulatory NOC power, my analysis has limitations. The main potential caveat is coming from the country panel model setting and the general complexity of macroeconomic variables. Even though I used two-way fixed-effect estimation which controls for country-level unobserved characteristics and included other controls as well, I could not rule out the existence of other potential factors behind the effects. However, I believe that my hypothesis and my analysis are valuable starting points for further work in the carbon curse theory.

[6] Although robustness checks revealed that the exact shape of the curve might be sensitive for the time frame and for the model setup.

In my opinion, there are several potential steps following this research. First, it is an important and interesting further analysis to understand which specific carbon curse channels are affected by the NOCs' regulatory settings the most. It could be that stronger institutional NOC power causes crowding out effect, lower renewable investments, increase in the energy subsidies or lower energy efficiency. Second, as I suggested previously, I could measure the monopolistic NOC-related conditional carbon curse with a more precise economic power metric. Third, with a different, field-level dataset a more rigid carbon curse and conditional carbon curse estimation could be made, although according to my research, there is no publicly available data source with field-level oil and gas production. Finally, in a case-study setting further analysis could investigate my conditional carbon curse hypothesis in specific countries.

Overall, this analysis provided an empirical estimation of the carbon curse and added an interesting layer, the effect of different National Oil Companies' settings, by investigating the heterogeneity among the main oil sector actors. Although my results have some limitations, it highlights an important potential aspect of the human-related CO2 emission. Given the fact, that mitigating human-related CO2 emission is a global effort, being capable to understand the socio-economic mechanisms, which influence countries' pollution, is a crucial step for environmental, economic, and political analysts.

Appendix

Table 6 T-test for emission intensity by resource dependency. Own calculation.

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	3,674	.2858288	.0044025	.2668527	.2771972	.2944604
1	657	.5343541	.0178167	.4566789	.4993693	.5693388
combined	4,331	.3235294	.004804	.3161518	.3141111	.3329476
diff		-.2485253	.0128496		-.2737171	-.2233334

```
    diff = mean(0) - mean(1)                                  t = -19.3411
Ho: diff = 0                                 degrees of freedom =     4329

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Note. Resource rich = 1, resource poor = 0. Resource rich means > 10% of GDP oil and gas production

Table 7 Average oil dependency in resource rich countries by regulatory NOC. Own calculation.

```
. ttest Oil_prod_GDP_real_ppp if res_rich == 1, by(rnoc)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	282	.2002603	.0084457	.1418271	.1836355	.2168852
1	375	.2001486	.006113	.1183775	.1881285	.2121688
combined	657	.2001966	.0050274	.1288625	.1903248	.2100683
diff		.0001117	.0101648		-.0198479	.0200713

```
    diff = mean(0) - mean(1)                                  t =   0.0110
Ho: diff = 0                                 degrees of freedom =      655

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.5044         Pr(|T| > |t|) = 0.9912          Pr(T > t) = 0.4956
```

Note. Regulatory NOC = 1, No regulatory NOC = 0. Resource rich means > 10% of GDP oil and gas production

Table 8 Average oil dependency in resource rich countries by monopolistic NOC. Own calculation.

```
. ttest Oil_prod_GDP_real_ppp if res_rich == 1, by(mpnoc)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |     278    .1945966    .0071413    .1190692    .1805385    .2086547
       1 |     379    .2043042    .0069656    .1356053     .190608    .2180003
---------+--------------------------------------------------------------------
combined |     657    .2001966    .0050274    .1288625    .1903248    .2100683
---------+--------------------------------------------------------------------
    diff |           -.0097075    .0101765                -.02969     .0102749
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -0.9539
Ho: diff = 0                                     degrees of freedom =      655

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.1702         Pr(|T| > |t|) = 0.3405          Pr(T > t) = 0.8298
```

Note. Monopolistic NOC = 1, Non-monopolistic NOC = 0. Resource rich means > 10% of GDP oil and gas production

Table 9 Within and between variances. Own calculation.

Variable	Mean	Std. Dev.	Min	Max	Observations
ln CO2/GDP	-1.475794	0.8354045	-6.247073	1.239842	N = 4331
between		0.7745519	-3.152687	0.246793	n = 131
within		0.3316705	-5.287731	0.1700804	T-bar = 33.0611
OilGas prod/GDP	0.0473982	0.1152118	0	1.802168	N = 4331
between		0.0979166	0	0.5836241	n = 131
within		0.064449	-0.4695759	1.265942	T-bar = 33.0611
Regulatory NOC	0.2313553	0.4217477	0	1	N = 4331
between		0.3889016	0	1	n = 131
within		0.1658619	-0.7400732	0.9396887	T-bar = 33.0611
Monopolistic NOC	0.1981067	0.398619	0	1	N = 4331
between		0.3659926	0	1	n = 131
within		0.1574517	-0.7602267	0.9981067	T-bar = 33.0611

ln GDP/capita	8.757808	1.210588	5.495883	12.6656	N = 4331
between		1.13689	6.703993	11.69325	n = 131
within		0.3770486	7.131513	10.55099	T-bar = 33.0611
ln Population	9.406428	1.402368	5.521185	14.15159	N = 4331
between		1.386824	6.30406	14.02215	n = 131
within		0.2083312	8.348499	10.54992	T-bar = 33.0611
CDD	5965.595	4503.571	3.4	16472.91	N = 4200
between		4504.439	43.78823	15034.32	n = 131
within		345.7934	4481.404	7404.18	T = 32.0611
HDD	6387.525	7208.964	0	33544.57	N = 4200
between		7473.605	0	29977.69	n = 131
within		572.6615	3523.717	10599.06	T = 32.0611
Polity	2.301089	7.005119	-10	10	N = 4316
between		5.936173	-10	10	n = 131
within		3.786382	-13.0132	14.75942	T-bar = 32.9466

Table 10 Hausmann tests for conditional carbon curses. Own calculation.

Ho: difference in coefficient is not systematic

Hausman Test	df	chi2(df)	Prob>chi2
Quadratic Regulatory NOC model (equation (3))	9	278.15	0
Linear Regulatory NOC model (equation (4))	7	291.69	0
Quadratic Monopolistic NOC model (equation (5))	9	252.57	0
Linear Monopolistic NOC model (equation (6))	7	292.17	0

Table 11 Pesaran's test for cross-sectional collinearity. Own calculation.

Pesaran's test of cross sectional independence	*coeff.*	*Pr.*
Quadratic Regulatory NOC model (equation (3))	-2.429,	0.0151
Linear Regulatory NOC model (equation (4))	-2.572,	0.0101
Quadratic Monopolistic NOC model (equation (5))	-2.260,	0.0238
Linear Monopolistic NOC model (equation (6))	-2.464,	0.0138

Table 12 Robustness check for a different time interval (1993 – 2013). Own calculation.

	(1)	(2)	(3)	(4)	(5)	(6)
	FE - Driscoll Kraay	FE - Driscoll Kraay	FE - Driscoll Kraay	FE - Driscoll Kraay	FE - Driscoll Kraay	FE - Driscoll Kraay
	Carbon Curse	Carbon Curse	Regulatory NOC	Regulatory NOC	Monopolistic NOC	Monopolistic NOC
Oil&gas prod per GDP	1.271***	0.646***	-1.020*	-0.581**	1.527***	0.679***
	(2.79e-08)	(1.06e-09)	(0.0546)	(0.0245)	(1.30e-06)	(2.74e-06)
Oil&gas prod per GDP * Regulatory NOC			3.522***	1.552***		
			(6.03e-07)	(1.14e-05)		
Oil&gas prod per GDP * Monopolistic NOC					-0.186	-0.177
					(0.820)	(0.574)
Oil&gas prod per GDP square	-0.570***		1.497*		-0.706***	
	(3.21e-07)		(0.0558)		(1.16e-05)	
Oil&gas prod per GDP * Regulatory NOC			-2.821***			
			(0.00112)			
Oil&gas prod per GDP square * Monopolistic NOC					-0.642	
					(0.509)	
ln per capita GDP	-0.571***	-0.564***	-0.596***	-0.568***	-0.578***	-0.565***
	(0)	(0)	(0)	(0)	(0)	(0)
ln population	0.408***	0.433***	0.382***	0.435***	0.405***	0.435***
	(4.39e-07)	(1.26e-07)	(3.60e-06)	(2.17e-07)	(2.95e-07)	(6.09e-08)
CDD	3.13e-05	3.38e-05	3.13e-05	3.46e-05	2.95e-05	3.33e-05
	(0.159)	(0.152)	(0.203)	(0.175)	(0.184)	(0.163)
HDD	2.43e-05**	2.47e-05**	2.18e-05**	2.38e-05**	2.47e-05**	2.49e-05**
	(0.0143)	(0.0118)	(0.0325)	(0.0174)	(0.0124)	(0.0101)
Polity index	0.00250	0.00208	0.00388*	0.00245	0.00257	0.00201
	(0.233)	(0.360)	(0.0579)	(0.309)	(0.240)	(0.378)
Constant	0	0	0	0	0	0
Observations	2,618	2,618	2,618	2,618	2,618	2,618
Number of countries	131	131	131	131	131	131
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
pval in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Table 13 Robustness check for base NOCs' characteristic. Own calculation.

	(1)	(2)	(3)	(4)
	FE - Driscoll Kraay	FE - Driscoll Kraay	FE - Driscoll Kraay	FE - Driscoll Kraay
	Regulatory NOC	Regulatory NOC	Monopolistic NOC	Monopolistic NOC
Oil&gas prod per GDP	0.241	0.168	1.844***	0.906***
	(0.572)	(0.350)	(8.14e-05)	(0.000313)
Regulatory NOC	-0.120***	-0.0439*		
	(1.23e-08)	(0.0623)		
Monopolistic NOC			-0.0192	0.0116
			(0.716)	(0.846)
Oil&gas prod per GDP * Regulatory NOC	2.060***	0.816***		
	(0.000368)	(0.000566)		
Oil&gas prod per GDP * Monopolistic NOC			-0.0192	-0.512
			(0.969)	(0.137)
Oil&gas prod per GDP square	0.0514		-0.725***	
	(0.904)		(0.00105)	
Oil&gas prod per GDP square * Regulatory NOC	-1.097**			
	(0.0265)			
Oil&gas prod per GDP square * Monopolistic NOC			-1.221***	
			(0.00644)	
ln_per_capita	-0.351***	-0.338***	-0.349***	-0.344***
	(2.49e-08)	(3.61e-08)	(2.67e-08)	(4.24e-08)
ln_population	0.651***	0.679***	0.614***	0.662***
	(9.96e-11)	(5.46e-11)	(1.15e-10)	(0)
CDD	2.31e-05**	2.61e-05***	1.83e-05*	2.24e-05**
	(0.0191)	(0.00967)	(0.0903)	(0.0373)
HDD	3.81e-05***	3.85e-05***	3.92e-05***	3.88e-05***
	(7.08e-05)	(2.55e-05)	(3.31e-05)	(2.22e-05)
Polity	-0.00499***	-0.00564***	-0.00516***	-0.00598***
	(0.00558)	(0.00259)	(0.00318)	(0.000972)
Constant	-4.685***	-5.055***	-4.369***	-4.843***
	(2.78e-05)	(1.14e-05)	(2.71e-05)	(1.07e-05)
Observations	4,186	4,186	4,186	4,186
Number of income groups	131	131	131	131
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
pval in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Table 14 Robustness check for a narrowed country group – Unit root test. Own calculation.

Pesaran's CADF test for	Z[t-bar]	P-value
ln CO2/GDP	-1.945	0.026
Oil&gas prod per GDP	-1.091	0.138
Diff(1) Oil&gas prod per GDP	-10.026	0.000
Diff(1) Oil&gas prod per GDP square	-14.116	0.000
ln GDP per capita	-0.265	0.396
Diff(1) ln GDP per capita	-6.893	0.000
ln population	-6.103	0.000
CDD	-5.836	0.000
HDD	-9.238	0.000
Polity	1.286	0.901
Diff(1) Polity	-4.67	0

Note. Diff(1) means the variable is differenced (taking the difference Yt - Yt-1) due to the fact that the level of the variable is non-stationer. After the subtraction, all the variables become stationer.

Table 15 Robustness check for a narrowed country group – Hausmann test. Own calculation.

Hausman Test	df	chi2(df)	Prob>chi2
Quadratic Carbon Curse model (equation (1))	7	40.18	0.00
Linear Carbon Curse model (equation (1))	6	35.21	0.00
Quadratic Regulatory NOC model (equation (3))	9	40.29	0.00
Linear Regulatory NOC model (equation (4))	7	38.21	0.00
Quadratic Monopolistic NOC model (equation (5))	9	47.2	0.00
Linear Monopolistic NOC model (equation (6))	7	37.67	0.00

Table 16 Robustness check for a narrowed country group – Pesaran's test. Own calculation.

Pesaran's test of cross-sectional independence	*coeff.*	*Pr.*
Quadratic Carbon Curse model (equation (1))	-2.01	0.0444
Linear Carbon Curse model (equation (1))	-2.002	0.0453
Quadratic Regulatory NOC model (equation (3))	-2.009	0.0445
Linear Regulatory NOC model (equation (4))	-1.987	0.0469
Quadratic Monopolistic NOC model (equation (5))	-2.012	0.0442
Linear Monopolistic NOC model (equation (6))	-1.998	0.0457

Table 17 Robustness check for a narrowed country group – Regression results. Own calculation.

	(1)	(2)	(3)	(4)	(5)	(6)
	FE-Dricoll-Kraay	FE-Dricoll-Kraay	FE-Dricoll-Kraay	FE-Dricoll-Kraay	FE-Dricoll-Kraay	FE-Dricoll-Kraay
	Carbon Curse	Carbon Curse	Regulatory NOC	Regulatory NOC	Monopolistic NOC	Monopolistic NOC
Diff(1) Oil&gas prod per GDP	0.791	0.646*	0.0846	0.445*	1.261	0.674
	(0.177)	(0.0838)	(0.857)	(0.0625)	(0.309)	(0.226)
Diff(1) Oil&gas prod per GDP * Regulatory NOC			0.881	0.257		
			(0.203)	(0.397)		
Diff(1) Oil&gas prod per GDP * Monopolistic NOC					-1.203	-0.0543
					(0.275)	(0.901)
Diff(1) Oil&gas prod per GDP square	-0.108		0.489		-0.340	
	(0.796)		(0.294)		(0.546)	
Diff(1) Oil&gas prod per GDP * Regulatory NOC			-0.680			
			(0.230)			
Diff (1) Oil&gas prod per GDP square * Monopolistic NOC					1.078	
					(0.120)	
Diff (1) ln per capita GDP	-0.226	-0.224	-0.234	-0.226	-0.215	-0.222
	(0.190)	(0.189)	(0.181)	(0.191)	(0.163)	(0.170)
ln population	0.557***	0.559***	0.560***	0.563***	0.554***	0.559***
	(6.23e-07)	(4.53e-07)	(7.19e-07)	(6.39e-07)	(5.12e-07)	(5.35e-07)
CDD	-6.62e-05**	-6.69e-05**	-6.49e-05**	-6.54e-05**	-6.54e-05**	-6.66e-05**
	(0.0321)	(0.0257)	(0.0289)	(0.0245)	(0.0319)	(0.0238)
HDD	6.00e-05***	6.03e-05***	5.96e-05***	6.04e-05***	6.10e-05***	6.06e-05***
	(0.000449)	(0.000301)	(0.000434)	(0.000278)	(0.000796)	(0.000677)
Diff (1) Polity index	0.000597	0.000668	0.000464	0.000650	0.00128	0.000724
	(0.933)	(0.925)	(0.948)	(0.927)	(0.855)	(0.917)
Constant	0	0	0	0	0	0
Observations	759	759	759	759	759	759
Number of countries	24	24	24	24	24	24
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
pval in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Note. 1 Diff(1) means the variable is differenced (taking the difference Yt - Yt-1) due to the fact that the level of the variable is non-stationer. As it is suggested in the Appendix Table 9. after this difference, the variables became stationer.

References

Al-mulali, U. (2012). *Factors affecting CO2 emission in the Middle East: A panel data analysis*. Energy, 44(1), 564–569. doi:10.1016/j.energy.2012.05.045

Al-Mulali, U.; Ozturk, I. (2015). *The effect of energy consumption, urbanization, trade openness, industrial output, and the political stability on the environmental degradation in the MENA (Middle East and North African) region*. Energy, 84(), 382-389. doi:10.1016/j.energy.2015.03.004

Al-Mulali, U.; Tang, C. F.; Ozturk, I. (2015). *Estimating the Environment Kuznets Curve hypothesis: Evidence from Latin America and the Caribbean countries*. Renewable and Sustainable Energy Reviews, 50(), 918–924. doi:10.1016/j.rser.2015.05.017

Andersen, J. J.; Ross, M. L. (2014). *The Big Oil Change: A Closer Look at the Haber-Menaldo Analysis*. Comparative Political Studies, 47(7), 993–1021. doi:10.1177/0010414013488557

Andersen, J.J.; Aslaksen, S. (2013). *Oil and political survival*. Journal of Development Economics, 100(1), 89 - 106. doi:10.1016/j.jdeveco.2012.08.008

Arezki, R.; Brückner, M. (2011). *Oil rents, corruption, and state stability: Evidence from panel data regressions*. European Economic Review, 55(7), 955–963. doi:10.1016/j.euroecorev.2011.03.004

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. doi:10.1016/j.resourpol.2016.10.015

Balsalobre-Lorente, D.; Shahbaz, M.; Roubaud, D.; Farhani, S. (2018). *How economic growth, renewable electricity and natural resources contribute to CO 2 emissions?*. Energy Policy, 113(), 356–367. doi:10.1016/j.enpol.2017.10.050

Bekun, F.V.; Alola, A.A.; Sarkodie, S.A. (2019). *Toward a sustainable environment: Nexus between CO2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries*. Science of The Total Environment, 657(), 1023–1029. doi:10.1016/j.scitotenv.2018.12.104

Bento, J.P.C.; Moutinho, V. (2016). *CO2 emissions, non-renewable and renewable electricity production, economic growth, and international trade in Italy*. Renewable and Sustainable Energy Reviews, 55(), 142–155. doi:10.1016/j.rser.2015.10.151

Brollo, F.; Nannicini, T.; Perotti, R.; Tabellini, G. (2013). *The Political Resource Curse. American Economic Review*, 103(5), 1759–1796. doi:10.1257/aer.103.5.1759

Coady, D.; Parry, I.; Sears, L. ; Shang, B. (2015). *How large are global energy subsidies ?*, IMF Working Paper, WP/15/105

Chiroleu-Assouline, M.; Fodha, M.; Kirat, Y. (2020). *Carbon curse in developed countries*. Energy Economics, 90(), 104829. doi:10.1016/j.eneco.2020.104829

Chiu, C.-L.; Chang, T.-H. (2009). *What proportion of renewable energy supplies is needed to initially mitigate CO2 emissions in OECD member countries?.* , 13(6-7), 1669–1674. doi:10.1016/j.rser.2008.09.026

Cialani, C. (2017). *CO2 emissions, GDP and trade: a panel cointegration approach*. International Journal of Sustainable Development & World Ecology, 24(3), 193–204. doi:10.1080/13504509.2016.1196253

Coşar, B.; Yilmaz, H.; Altindağ, E. (2019). *The Role of State-Owned Enterprises in an Artificial Monopoly Market: The Case of Turkey.* American Journal of Economics and Sociology, *78(5), 1171–1199.* doi:10.1111/ajes.12299

Cust, J.; Mihalyi, D. (2017). *Evidence for a Presource Curse? : Oil Discoveries, Elevated Expectations, and Growth Disappointments*. Policy Research Working Paper No. 8140. World Bank

Dietz, T.; Rosa, E. A. (1997). *Effects of population and affluence on CO2 emissions. Proceedings of the National Academy of Sciences.*, 94(1), 175–179. doi:10.1073/pnas.94.1.175

Holtz-Eakin, D.; Selden, T. M. (1995). *Stoking the fires? CO2 emissions and economic growth.* , 57(1), 85–101. doi:10.1016/0047-2727(94)01449-x

Driscoll, J. C.; Kraay, A. C. (1998). *Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. Review of Economics and Statistics*, 80(4), 549–560. doi:10.1162/003465398557825

Eller, S. L.; Hartley, P. R.; Medlock, K. B.(2011). *Empirical evidence on the operational efficiency of National Oil Companies.*, 40(3), 623–643. doi:10.1007/s00181-010-0349-8

Friedrichs, J.; Inderwildi, O. R. (2013). *The carbon curse: Are fuel rich countries doomed to high CO2 intensities?.* Energy Policy, 62(), 1356–1365. doi:10.1016/j.enpol.2013.07.076

Grossman, G. M; Krueger, A. B. (1991). *Environmental Impacts of a North American Free Trade Agreement*. National Bureau of Economic Research Working Paper Series, No. 3914(3914), 1–57. doi:10.3386/w3914

Gylfason, T. (2001). *Natural resources, education, and economic development*. European Economic Review, 45(4-6), 847–859. doi:10.1016/s0014-2921(01)00127-1

Gylfason, T.; Zoega, G.(2006). *Natural Resources and Economic Growth: The Role of Investment.*, 29(8), 1091–1115. doi:10.1111/j.1467-9701.2006.00807.x

Hashmi, R.; Alam, K. (2019). *Dynamic relationship among environmental regulation, innovation, CO2 emissions, population, and economic growth in OECD countries: A panel investigation*. Journal of Cleaner Production, 231(), 1100-1109. doi:10.1016/j.jclepro.2019.05.325

Heller, P. R. P.; Mihalyi, D. (2019). *Massive and Misunderstood Data-Driven Insights into National Oil Companies*. Natural Resource Government Institute

Hoechle, D. (2007). *Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence.* The Stata Journal: Promoting communications on statistics and Stata, 7(3), 281–312. doi:10.1177/1536867X0700700301

Hwang, Y.; Um, J.-S.; Hwang, J.; Schlüter, S. (2020). *Evaluating the Causal Relations between the Kaya Identity Index and ODIAC-Based Fossil Fuel CO2 Flux*. Energies, 13(22), 6009. doi:10.3390/en13226009

Iimi, A. (2007). *Escaping from the Resource Curse: Evidence from Botswana and the Rest of the World*. IMF Staff Papers, 54(4), 663–699. doi:10.2307/30035929

Ike, G. N.; Usman, O.; Asumadu-Sarkodie, S. (2019). *Testing the Role of Oil Production in the Environmental Kuznets Curve of Oil Producing Countries: New insights from Method of Moments Quantile Regression*. Science of The Total Environment, 1;711:135208. doi:10.1016/j.scitotenv.2019.135208

IPCC (2000). *Emission Scenarios.* Nakicenovic, N.; Swart, R. (Eds.) Cambridge University Press

IPCC (2014). *Climate Change 2014: Synthesis Report*. *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Pachauri, R.K.; Meyer, L.A. (Eds.). IPCC

Kaya, Y. (1990). *Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios*. IPCC Response Strategies Working Group Memorandum 1989. IPCC Energy and Industry Subgroup, Response Strategies Working Group.

Lee, H. (2020). *Energy is at the heart of the solution to the climate challenge*. ipcc.ch. Retrieved May 25, 2021, from: https://www.ipcc.ch/2020/07/31/energy-climatechallenge/

Lee, J. W.; Brahmasrene, T. (2013). *Investigating the influence of tourism on economic growth and carbon emissions: Evidence from panel analysis of the European Union*. Tourism Management, 38(), 69–76. doi:10.1016/j.tourman.2013.02.016

Liu, H.; Kim, H.; Choe, J. (2019). *Export diversification, CO2 emissions and EKC: panel data analysis of 125 countries*. Asia-Pacific Journal of Regional Science, 3(2), 361–393. doi:10.1007/s41685-018-0099-8

Mahdavi, P. (2020a). *Institutions and the "Resource Curse": Evidence From Cases of Oil-Related Bribery*. Comparative Political Studies, 53(1), 3-39. doi:10.1177/0010414019830727

Masnadi, M. S.; El-Houjeiri, H. M.; Schunack, D.; Li, Y.; Englander, J.G.; Badahdah, A.; Monfort, J.-C.; Anderson, J. E.; Wallington, T. J.; Bergerson, J.A.; Gordon, D.; Koomey, J.; Przesmitzki, S.; Azevendo, I. L.; Bi, X. T.;Duffy, J. E.; Heath, G. A.; Keoleian, G. A.; McGlade, C.; Meehan, D. N.; Yeh, S.; You, F.; Wang, M.; Brandt, A. (2018). *Global carbon intensity of crude oil production*. Science, 361(6405), 851-853. doi: 10.1126/science.aar6859

Mardani, A.; Streimikiene, D.; Cavallaro, F.; Loganathan, N.; Khoshnoudi, M. (2018). *Carbon dioxide (CO2) emissions and economic growth: A systematic review of two decades of research* *from 1995 to 2017*. Science of The Total Environment, 649(), 31-49. doi:10.1016/j.scitotenv.2018.08.229

Mavragani, A.; Nikolaou, I.; Tsagarakis, K. (2016). *Open Economy, Institutional Quality, and Environmental Performance: A Macroeconomic Approach. Sustainability*, 8(7), 601. doi:10.3390/su8070601

Mehlum, H.; Moene, K.; Torvik, R.(2006). *Institutions and the Resource Curse*. The Economic Journal, 116(508), 1–20. doi:10.1111/j.1468-0297.2006.01045.x

Neumayer, E. (2002). *Can natural factors explain any cross-country differences in carbon dioxide emissions?*. Energy Policy, 30(1), 7–12. doi:10.1016/s0301-4215(01)00045-3

Özokcu, S.; Özdemir, Ö. (2017). *Economic growth, energy, and environmental Kuznets curve*. Renewable and Sustainable Energy Reviews, 72(), 639–647. doi:10.1016/j.rser.2017.01.059

Papyrakis, E.; Gerlagh, R. (2004). *The resource curse hypothesis and its transmission channels*. Journal of Comparative Economics, 32(1), 181–193. doi:10.1016/j.jce.2003.11.002

Pesaran, M. H. (2021). *General diagnostic tests for cross-sectional dependence in panels.* Empirical Economics, Springer, 60(1), 13-50. DOI: 10.1007/s00181-020-01875-7

Sims, R.E.H.; Schock, R.N.; Adegbululgbe, A.; Fenhann, J.; Konstantinaviciute, I.; Moomaw, W.; Nimir, H.B.; Schlamadinger, B.; Torres-Martínez, J.; Turner,C.; Uchiyama,Y.; Vuori, S.J.V.; Wamukonya,N.; Zhang, X. (2007). *Energy supply*. In Metz, B.; Davidson, O.R.; Bosch, P.R.; Dave, R., Meyer, L.A. (Eds). *Climate Change: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press

Ramsay, K. W. (2011). *Revisiting the Resource Curse: Natural Disasters, the Price of Oil, and Democracy*. International Organization, 65(3), 507–529. doi:10.1017/S002081831100018X

Riaño, J.; Hodess, R. (2008). *Bribe Payers Index 2008*. Transparency International

Ritchie, H. (n.d.). *Energy mix*. Retrieved May 25, 2021, from: https://ourworldindata.org/energy-mix#direct-vs-substituted-primary-energy-what-are-the-multiple-ways-of-energy-accounting

Rofiuddin, M.; Aisyah, S.; Pratiwi, D. N.; Annisa, A. A.; Puspita, R. E.; Nabila, R. (2019). *Does Economic Growth Reduce Pollution? Empirical Evidence from Low Income Countries*. E3S Web of Conferences, 125(), 06002. doi:10.1051/e3sconf/201912506002

Ross, M. L. (2015). *What Have We Learned about the Resource Curse?.* Annual Review of Political Science, 18(), 239–259. doi:10.1146/annurev-polisci-052213-040359

Sachs, J. D.; Warner, A. M. (1995). *Natural Resource Abundance and Economic Growth*. National Bureau of Economic Research Working Paper Series, No.5398. doi:10.3386/w5398

Sarkodie, S. A.; Strezov, V. (2018). *Empirical study of the Environmental Kuznets curve and Environmental Sustainability curve hypothesis for Australia, China, Ghana and USA*. Journal of Cleaner Production, 201(), 98–110. doi:10.1016/j.jclepro.2018.08.039

Shahbaz, M.; Tang, C. F.; Shahbaz Shabbir, M. (2011). *Electricity consumption and economic growth nexus in Portugal using cointegration and causality approaches.* Energy Policy, 39(6), 3529–3536. doi:10.1016/j.enpol.2011.03.052

Stern, D. I.; van Dijk, J. (2017). *Economic growth and global particulate pollution concentrations*. Climatic Change, 142(3-4), 391–406. doi:10.1007/s10584-017-1955-7

Sulemana, I.; James, H. S.; Rikoon, J. S. (2016). *Environmental Kuznets Curves for air pollution in African and developed countries: exploring turning point incomes and the role of democracy*. Journal of Environmental Economics and Policy, 6(2), 134–152. doi:10.1080/21606544.2016.1231635

Tordo, S.; Tracy, B. S.; Arfaa, N. (2011). *Natural Oil Companies and Value Creation*. World Bank Working Paper, No. 218. World Bank.

Tsui, K. K.(2011). More Oil, Less Democracy: Evidence from Worldwide Crude Oil Discoveries., 121(551), 89–115. doi:10.1111/j.1468-0297.2009.02327.x

UN (2015). *Paris Agreement*. FCCC/CP/2015/10/Add.1. Retrieved May 25, 2021, from https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

Usman, O.; Iorember, P. T.; Olanipekun, I. O. (2019). *Revisiting the environmental Kuznets curve (EKC) hypothesis in India: the effects of energy consumption and democracy*. Environmental Science and Pollution Research, 26(), 13390–13400. doi:10.1007/s11356-019-04696-z

van der Ploeg, F. (2011). *Natural Resources: Curse or Blessing?*. Journal of Economic Literature, 49(2), 366–420. doi:10.1257/jel.49.2.366

van der Ploeg, F.; Poelhekke, S. (2009). *Volatility and the natural resource curse*. Oxford Economic Papers, 61(4), 727–760. doi:10.1093/oep/gpp027

Victor, D. G. (2013). *National Oil Companies and the Future of the Oil Industry*. Annual Review of Resource Economics, 5(), 445–462. doi:10.1146/annurev-resource-091912-151856

Victor, N. M. (2007). *On Measuring the Performance of National Oil Companies*—Program on Energy and Sustainable Development Working Paper #64

Wang, K.; Wu, M.; Sun, Y.; Shi, X.; Sun, A.; Zhang, P. (2019). *Resource abundance, industrial structure, and regional carbon emissions efficiency in China*. Resources Policy, 60(), 203–214. doi:10.1016/j.resourpol.2019.01.001

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.

Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach* (5th ed.). Cengage Learning.

Datasets

Feenstra, Robert C.; Inklaar, R.; Timmer, M. P. (2015). *The Next Generation of the Penn World Table*. American Economic Review, 105(10), 3150-3182. doi: 10.15141/S5Q94M

Friedlingstein, P.; O'Sullivan, M.; Jones, M. W.; Andrew, R. M.; Hauck, J.; Olsen, A.; Peters, G. P.; Peters, W.; Pongratz, J.; Sitch, S.; Le Quéré, C.; Canadell, J. G.; Ciais, P.; Jackson, R. B.; Alin, S.; Aragão, L. E. O. C.; Arneth, A.; Arora, V.; Bates, N. R.; Becker, M.; Benoit-Cattin, A.; Bittig, H. C.; Bopp, L.; Bultan, S.; Chandra, N.; Chevallier, F.; Chini, L. P.; Evans, W.; Florentie, L.; Forster, P. M.; Gasser, T.; Gehlen, M.; Gilfillan, D.; Gkritzalis, T.; Gregor, L.; Gruber, N.; Harris, I.; Hartung, K.; Haverd, V.; Houghton, R. A.; Ilyina, T.; Jain, A. K.; Joetzjer, E.; Kadono, K.; Kato, E.; Kitidis, V.; Korsbakken, J. I.; Landschützer, P.; Lefèvre, N.; Lenton, A.; Lienert, S.; Liu, Z.; Lombardozzi, D.; Marland, G.; Metzl, N.; Munro, D. R.; Nabel, J. E. M. S.; Nakaoka, S.-I.; Niwa, Y.; O'Brien, K.; Ono, T.; Palmer, P. I.; Pierrot, D.; Poulter, B.; Resplandy, L.; Robertson, E.; Rödenbeck, C.; Schwinger, J.; Séférian, R.; Skjelvan, I.; Smith, A. J. P.; Sutton, A. J.; Tanhua, T.; Tans, P. P.; Tian, H.; Tilbrook, B.; van der Werf, G.; Vuichard, N.; Walker, A. P.; Wanninkhof, R.; Watson, A. J.; Willis, D.; Wiltshire, A. J.; Yuan, W.; Yue, X.; and Zaehle, S. (2020). *Global Carbon Budget 2020*. Earth Syst. Sci. Data, 12, 3269–3340. https://doi.org/10.5194/essd-12-3269-2020

Kapsarc (n.d.). *Global Degree-Days Database*. Kapsarc.org. Retrieved May 25th, 2021 from: https://www.kapsarc.org/research/projects/global-degree-days-database/

Mahdavi, P. (2020b). *Power Grab: Political Survival through Extractive Resource Nationalization*. Cambridge, UK and New York, NY: Cambridge University Press.

Marshall, M. G.; Gurr, T. R. (2018). *POLITY5. Political Regime Characteristics and Transitions, 1800-2018*. Dataset Users' Manual

Ross, M.; Mahdavi, P. (2015). *Oil and Gas Data, 1932-2014*. Harvard Dataverse. https://doi.org/10.7910/DVN/ZTPW0Y.

United Nations, Department of Economic and Social Affairs, Population Division (2019). *World Population Prospects 2019*, Online Edition. Rev. 1.