UNIVERSITA' DEGLI STUDI DI PADOVA

DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI "M.FANNO"

CORSO DI LAUREA MAGISTRALE IN ECONOMICS AND FINANCE

TESI DI LAUREA

"The Drivers of CO_2 Emissions Before and After the Great Recession: A Decomposition Analysis"

RELATORE:

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MATRICOLA N. 1206053

ANNO ACCADEMICO 2019 – 2020

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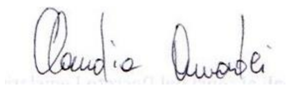

Acknowledgements

I would like to thank my Thesis advisor, for the precious help and insights given, and for the constant availability and support, even in such unusual times.

I would like to thank all of my family, without whom I would not have been able to do any of this, and for always giving me self-esteem boosts whenever I needed it.

I would like to thank all my friends, for putting up with me and my absolutely motivated anxieties for all this time.

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INTRODUCTION

The Amazon burning. Hurricane Laura. East Africa drought. Australian wildfires. These are just a few of the many natural disasters that have made it to newspaper headlines, ultimately leading to 2019 being labelled as the Year of "climate strike". It is straightforward, now more than ever, that the current economic development is at odds with environmental protection. The linkage between economic growth and environmental degradation has been evident since the beginning of the Eighteenth-Century Industrial Revolution. Back then, environmental degradation would show up in the form of thick layers of smog, blackening buildings and damaging people's health. Despite the fact that the fuel mix and the energy utilization became undeniably more efficient through the years, aided by technological developments, the link between economic development and environmental pressure is still there. This becomes especially relevant during periods of Recession, which, alongside economic degradation, generally show a slow-down in emissions growth.

It is in this last statement that lays the purpose of this work. Indeed, by means of a Kaya decomposition into their four driving factors, namely population, energy intensity of GDP, carbon intensity of energy, and GDP per capita, changes in energy-related CO_2 emissions will be analysed for period 1990-2017 in the World's top five emitting countries, namely China, United States, Europe, India and Russian Federation, where, for Europe, three countries will be selected, namely Germany, United Kingdom and Italy. By subdividing the entire time window into four subperiods, namely 1990-1999, 2000-2007, 2008-2012, 2013-2017, the interplay between the four driving factors across the different subperiods will be analysed in deep. By doing so, and accompanying the decomposition with a decoupling analysis, it will be possible to discern how, and whether, the relationship between the indicator used for environmental degradation, i.e., energy-related CO_2 emissions, and the one used for economic development, i.e., GDP per capita, has been affected by the advent of the Great Recession.

This kind of analysis is relevant now more than ever, since, by entering a crisis whose consequences are already proving to be far worse than those of the Great Recession, the issue of overcoming an economic downturn without compromising the environment is extremely important. As a matter of fact, history seems to be repeating itself. Indeed, during the Great Recession, total emissions experienced a significant reduction between 2007 and 2009, caused, according to Worland (2015), for more than its 80%, by the economic downturn. In the current situation, the lockdowns imposed in many countries worldwide and the consequent drop in economic activities have already caused, in the short term, major impacts on the environment, with greenhouse gas emissions from transportation and industrial activity experiencing major drops and IEA estimating 2020 emissions to be 8% lower than in 2019 (OECD, 2020). Nevertheless, currently the priority is on overcoming the health crisis and relieving affected businesses and workers. It is because of this reason that the OECD (2020) advocates for policy regard towards the environmental impact of recovery measures, viewing the current situation as an "opportunity to more closely align public policies with climate objectives and limit the risk of locking-in carbon-intensive infrastructure". Indeed, as further explored in this study, a process of economic recovery does not need to necessarily compromise the environment, as, to some lengths, occurred in the period following the Great Recession, characterized by progressive decoupling between environmental degradation and economic growth.

This work is organized as follows. Chapter 1 presents an overview of the phaenomena of Global Warming and Climate change and motivates the choice of focusing on energy-related anthropogenic CO_2 emissions. Chapter 2, after a brief literature review on Kaya decomposition and the main decomposition techniques, moves on to the LMDI I decomposition analysis of energy-related CO_2 emissions in the period 1990-2017 for Germany, United Kingdom, Italy, United States, China, India and Russian Federation. After a brief theoretical explanation, a Tapio decoupling analysis follows, in order to address the progressive relationship between energy-related CO_2 emissions and GDP per capita. Chapter 3 focuses on two driving factors for CO_2 emissions, namely energy intensity of GDP and carbon intensity of energy. The former is addressed by a Fisher Ideal index decomposition analysis for the years between 2000 and 2016, and by an LMDI I decomposition of industrial energy consumption, followed by a Tapio decoupling analysis of the same variable. The latter is addressed by analysing the change in the fuel mixes of the studied countries in the period 1990-2017. The Final Remarks conclude the work, summing up the main findings.

CHAPTER 1: FOSSIL FUEL-CO_2 EMISSIONS AND ANTHROPOGENIC GHG EMISSIONS

1.1. GHG emissions and the greenhouse gas effect

The Earth is unequivocally warming (Figure 1). The average surface temperature has increased by 0.8°C between the 20th and 21st century, with the majority of this change occurring in the past thirty years (National Research Council, 2010).

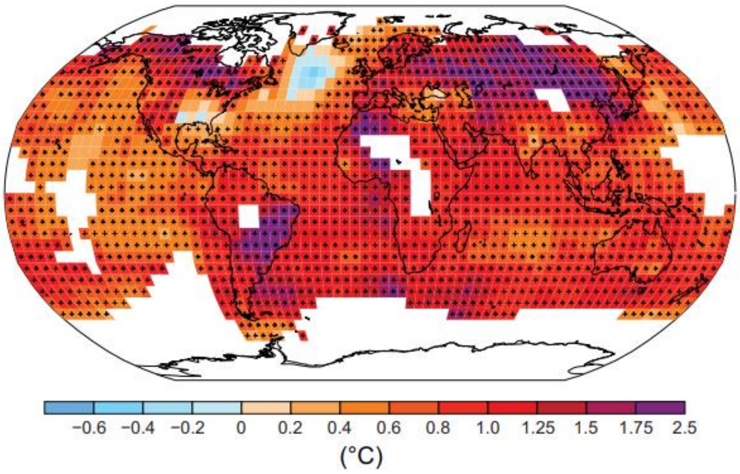

Figure 1 - Global observed change in surface temperature, 1901-2012. Source: IPCC, 2013.

On top of that, other severe consequences have occurred: ice has been melting, reducing the amount of overall glaciers around the world; sea levels have been rising, more so at a faster rate in the recent years; wildlife and ecosystems have been affected and extreme weather events (e.g. severe floods and droughts) became much more frequent (National Geographic, 2020). All those concurring facts have led to scientific consensus regarding the existence of the phaenomenon referred to as “Climate Change”, which is defined as the “long-term change in the average weather patterns that have come to define Earth’s local, regional and global climates” (NASA, 2020). This term is much broader and, unlike popular beliefs, not a synonym, of “Global Warming” as it encompasses both man-made and natural warming, and their effects, that include all the previously mentioned impacts.

Although it is hard to get to the root of this phaenomenon, as many concurring events could have contributed to its development, the National Research Council’s work (2010) linked the development of Climate Change to human activity. As a matter of fact, there has been a concurrency of the warming phaenomenon with an increase in human activities releasing Carbon Dioxide (CO_2) and other greenhouse gases (GHGs), and it has been so since the

Industrial Revolution in the Eighteenth Century (IPCC, 2013). For instance, Carbon Dioxide concentrations increased by 40% since pre-industrial levels, with the oceans absorbing about 30% of this increase, which resulted in ocean acidification. In this sense, as stated by the Intergovernmental Panel on Climate Change (IPCC, 2013), natural and anthropogenic substances which alter the Earth's energy balance, including therefore GHG emissions, are one of the main causes of Climate Change. Despite the worldwide deployment of regulations and GHG reduction targets, the increase in the emissions of such gases is ongoing, and what appears to be the most attainable goal, at this point, is the mere containment in their growth rates.

GHGs are of particular relevance in the definition of the causes of Climate Change because of the fact that they induce the so-called Greenhouse Effect (National Research Council, 2010), which consists in solar radiations failing to be reflected back to the atmosphere due to the presence of heat-trapping gases, namely GHGs (Figure 2). This is a phaenomenon that exists in nature, and is fundamental for life in this planet, as this heat trapping is necessary to maintain the Earth's normal living conditions. However, recent trends in the increase of GHG emissions have led this warming effect way beyond the level that would be naturally desirable. This caused an amplification of the natural Greenhouse Effect that, as previously highlighted, resulted in an increase in Earth's temperature.

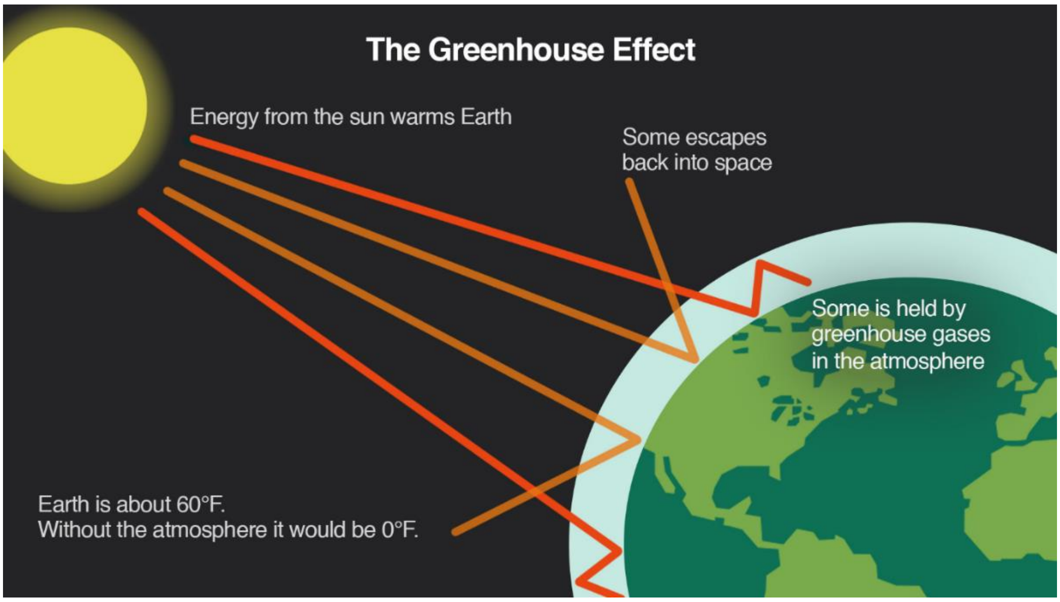

Figure 2 - Greenhouse Effect. Source: Climate Central, 2014.

However, the scope of what follows is not a thorough explanation of the Greenhouse Effect, but rather a focus on its leading causes.

To begin, the GHGs here tackled are the ones that have been listed in the Kyoto Protocol, namely Carbon Dioxide (CO_2), Methane (CH_4), Nitrous Oxide (N_2O) and Fluorinated gases

(Yue and Gao, 2018). However, before deepening the explanation of each of these components a fundamental distinction must be made, that is the one between natural and anthropogenic GHG emissions.

Indeed, GHGs can be found in nature, and some of their emissions arise from natural phaenomena. These are, for instance (Yue and Gao, 2018):

- ***Forest fires*** that, when nature-driven, are caused by droughts, heat and lighting. During these events the GHG emissions are huge and, for about 90%, are made up by CO_2. These events are the most relevant component of natural GHG emissions, accounting for almost 38% of their total.
- ***Oceans*** are an important carbon reservoir. They act, at the same time, as carbon sources and sinks and are, as a consequence, essential when dealing with GHGs management.
- ***Wetlands*** that, just like oceans, act as a carbon sink, but are, concurrently, a major source of CH_4 emissions, with a contribution to the overall annual emissions of this gas that can reach 15-30 percentage points.
- ***Permafrost*** is a natural ecosystem present in regions such as Siberia and Canada. This system happens to be a contributor to GHG emissions of, for instance, Carbon Monoxide (C), CO_2, CH_4 and N_2O.
- ***Volcanic eruptions and intermittent volcanoes*** are another relevant source of natural GHG emissions, mainly of CO_2 and CH_4.
- ***Mud volcanoes*** are volcanoes characterized by the eruption of mud. Their emissions are primarily of CH_4, which accounts for an approximate 95% contribution to the overall GHG emissions from mud volcanoes.
- ***Earthquakes*** are the last natural cause of GHG emissions here tackled. With the occurrence of these events, in fact, GHGs are emitted from the Earth and from the decay of animals and plants that are submersed after the earthquake.

On the other hand, also human activities exert a major contribution to the increase in GHG emissions. The explanation of the main emitting sectors that follows is based on the findings of the IPCC Working Group I (2013):

- The ***Energy Sector*** is the largest contributor to the increase of anthropogenic GHG emissions. In particular, fossil-fuel combustion constitutes the main cause of anthropogenic CO_2 emissions, as will be further explored in the following section. In general, it can be stated that energy demand has been on the rise, as can be demonstrated by the fact that per-capita primary energy use increased by 31% in the period 1971-

2010, with substantial differences among the developed economies, that experienced a much lower increase, and the developing ones. This increased need for energy clearly resulted in an increase in energy-related emissions.

- Another big contributor to anthropogenic GHG emissions is the sector of ***Agriculture, Forestry, and other Land Use***, whose emissions increased by 20% in 2010, with respect to the 9.9 GtCO_2eq level of 1970. Drivers of emissions in these sectors include increased livestock numbers, fertilizer's use, deforestation, and increased demand for food and animal products.
- The ***Transportation Sector***'s GHG emissions increased hugely (from 2.8 GtCO_2eq to 7 GtCO_2eq) in the period 1970-2010. This increase has been driven by developed economies for the majority, although with a progressively declining contribution (from 60% in 1970 to 46% in 2010).
- Of a lower extent was the increase in the ***Building Sector***'s emissions, that went from 2.5 GtCO_2eq in 1970 to 3.5 GtCO_2eq in 2010. The biggest contributors are still the developed economies of OECD-1990, despite a negative growth recorded in recent years.
- Direct GHG emissions from ***Industry*** have grown from 5.4 GtCO_2eq/yr in 1970 to 8.8 GtCO_2eq/yr in 2010. In this case, however, there has been a shift for what regards the countries contributing to this increase. In fact, while OECD-1990 countries were the biggest contributors, with a 57% share, in 1970, the progressive industrialization of developing economies that followed has led to a decline in this number, down to 24% in 2010. In this sector, of particular relevance for GHG emissions is the production of energy-intensive industrial goods, such as steel, cement and aluminium.
- The last contributing sector is the one of ***Waste***, whose global emissions almost doubled between 1970 and 2010. However, their relative share on the overall anthropogenic GHG emissions has remained relatively stable, as in 1970 GHG emissions from waste accounted for a 2.6% of the total GHG emissions, whereas in 2010 for a 3%. These emissions are connected to population growth, urbanization and affluence.

In order to give a representation of the relative contributions of each of these sectors, a graph from IPCC (2014) is reported below, representing the data of anthropogenic GHG emissions by sector for the year 2010.

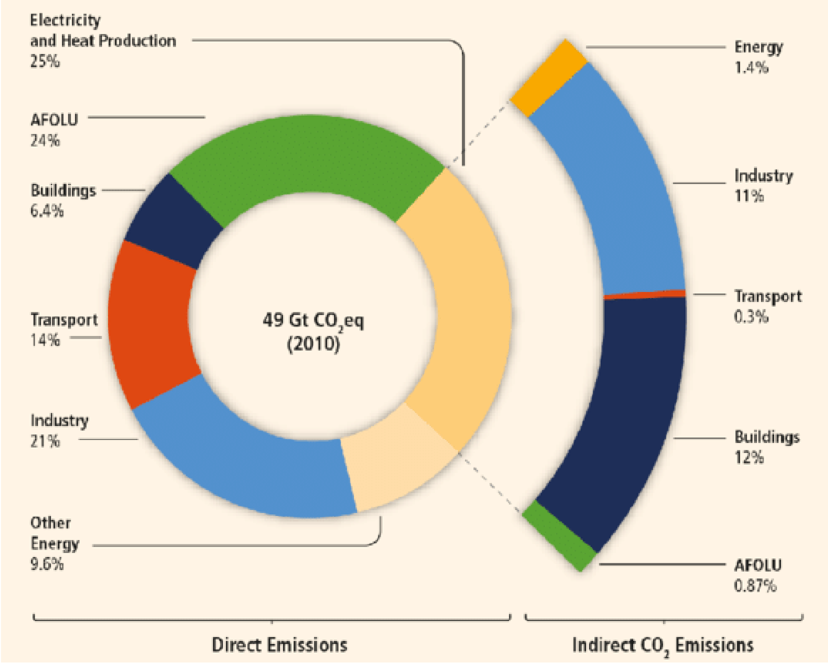

Figure 3 - Anthropogenic GHG emissions by Economic Sector. Source: IPCC, 2014.

Figure 3 shows that the sector of Electricity and Heat Production accounts for the largest portion of the overall anthropogenic GHG emissions, with a 25% share. However, it must be noted that most of the electricity and heat produced have the other sectors as beneficiaries. Accounting for this consideration, the actual contribution of the energy sector would really be minimal, with a mere 1.4% share.

After providing a definition of the two typologies of GHG emissions, it is useful to give an idea of their relative importance. Estimates made by Yue and Gao (2018), based on data collected from a number of studies made by entities like IPCC, The Global Carbon Budget and the UNFCCC, found that, out of the total annual global GHG emissions of 2016, that are in the range between 54.26 and 75.43 $GtCO_2eq$, the ratio of natural to anthropogenic emissions is between 0.5 and 1.09, with a most likely value of 0.8. This seems to point to the fact that the two are almost of the same order of magnitude. However, one fundamental distinction must be considered, that is the self-balancing property of the natural system. In fact, the carbon capturing activity enacted by oceans and vegetation allows for an absorption of the natural GHG emissions of roughly the same entity as their generation. This means that anthropogenic GHG emissions are the factor that exerts some extra pressure on the Earth's system and, therefore, the one that should be limited.

A formalization of this fact can be provided by the concept of Radiative Forcing, defined by IPCC (2013) as the net change in the Earth's energy balance caused by changes in "natural and anthropogenic substances and processes". Given that one of Earth's responses to these energy imbalances is an increase in its temperature, the concept of Radiative Forcing is quite relevant when considering the Climate Change phaenomenon. In this sense, by examining satellite observations of total solar irradiance changes, the IPCC assessment (2013) concluded that, as a whole, radiative forcing from changes in total solar irradiance has been of 0.05 W m^{-2} in the Industrial Era, i.e., the years from 1750 to 2011. Also, radiative forcing from volcanoes has been estimated for -0.11 in the years 2008-2011 when compared to 1750. On the other hand, the total anthropogenic radiative forcing for the Industrial Era has been estimated for about 2.3 W m^{-2}, which confirms that, even if natural and anthropogenic emissions may be of roughly the same order, the overall natural forcing is actually only a small portion of the anthropogenic one. This can be easily demonstrated by considering that, in the years between 1980 and 2011, the change in the natural forcing caused by the two factors mentioned (i.e. solar irradiance and volcanic phaenomena) was almost null, whereas the anthropogenic radiative forcing has increased of 1.0 W m^{-2} in the same period. More specifically, the natural forcing in the last 15 years has offset a fraction of about 30% of the anthropogenic one.

In short, it can be said that anthropogenic emissions are the ones that mostly contribute to the phaenomenon of Climate Change, while natural emissions appear to be basically self-balancing. For this reason, other than for the fact that measurement of the former type of emissions has much lower associated uncertainties, from now onwards, only anthropogenic GHG emissions will be considered.

1.2. Anthropogenic GHG emissions

Total anthropogenic emissions have been on the rise from the post-Industrial period, as a consequence of the increase in urbanization, human activities and industrialization. The largest growth has occurred in the last decades, with total anthropogenic emissions reaching their highest levels in history in the years between 2000 and 2010 (IPCC, 2014).

In particular, it is worth distinguishing among the different types of GHGs that have been listed in the previous Section (IPCC, 2014; Olivier and Peters, 2020):

- ***Carbon Dioxide*** (CO_2) accounts for the majority of anthropogenic GHG emissions. Furthermore, it is the gas that experienced the largest increase in the most recent years among all anthropogenic GHGs, as its emissions more than doubled between 1970 and 2010. CO_2 is mainly released through fossil fuel combustion, cement production, and “forestry and other land use”, a term that basically incorporates “forest fires, peat fires and peat decay" (IPCC, 2014). Specifically, CO_2 emissions from fossil fuel combustion and industrial processes make up the largest component of anthropogenic GHG emissions, accounting for about 65% of the total in 2010, whereas, in the same year, CO_2 emissions from forestry and other land use contributed to a 11% share.

- ***Methane*** (CH_4) is the second most relevant anthropogenic GHG emissions source, with a 16% share over the total in 2010. It is mainly originated from: agriculture and livestock, fossil fuel production and transmission (i.e. natural gas, oil, coal), and waste decay. The majority of CH_4 emissions arises from fossil fuel production and transmission, and from livestock, namely from emissions caused by ruminants, particularly cattle. In fact, referring to 2018 data collected from Olivier and Peters (2020), both of those factors accounted on a standalone basis for about a third of the total anthropogenic CH_4 emissions.
- ***Nitrous Oxide*** (N_2O) is the third most relevant source of anthropogenic GHG emissions, with a share of 6.2% in 2010. N_2O anthropogenic emissions arise mainly in the context of agricultural activities, that, in 2018, made up about 65% of their total. Some activities worth mentioning in this area are animal manure droppings and the use of synthetic nitrogen fertilizer. Smaller and actually declining contributions come from industrial processes, such as chemicals production, where the development of abatement technologies brought to a 48% reduction in their global N_2O emissions after peaks experienced in 1979, 1997 and 2007.
- ***Fluorinated gases*** (F-gases) include hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulphur hexafluoride (SF_6). Although their share on the overall anthropogenic GHG is relatively low, accounting for a 2 % contribution in 2010, these are known as High Global Warming Potential gases and are therefore still exerting a major pressure on the Earth's balance. The largest source of these gases is their use as substitutes of ozone-depleting substances, contributing in 2018 to two thirds of the total F-gases anthropogenic emissions. Among them, HFCs and SF_6 are the main F-gases deployed, with respective shares of 81% and 13% in 2018. Furthermore, HFCs experienced a major increase in the early 1990s, as a consequence of the Montreal Protocol-led prohibition of ozone-layer damaging gases such as hydrochlorofluorocarbons (HCFCs) and chlorofluorocarbons (CFCs).

Figure 4 illustrates the shares of the different anthropogenic GHG groups tackled and their evolution from 1970 to 2010.

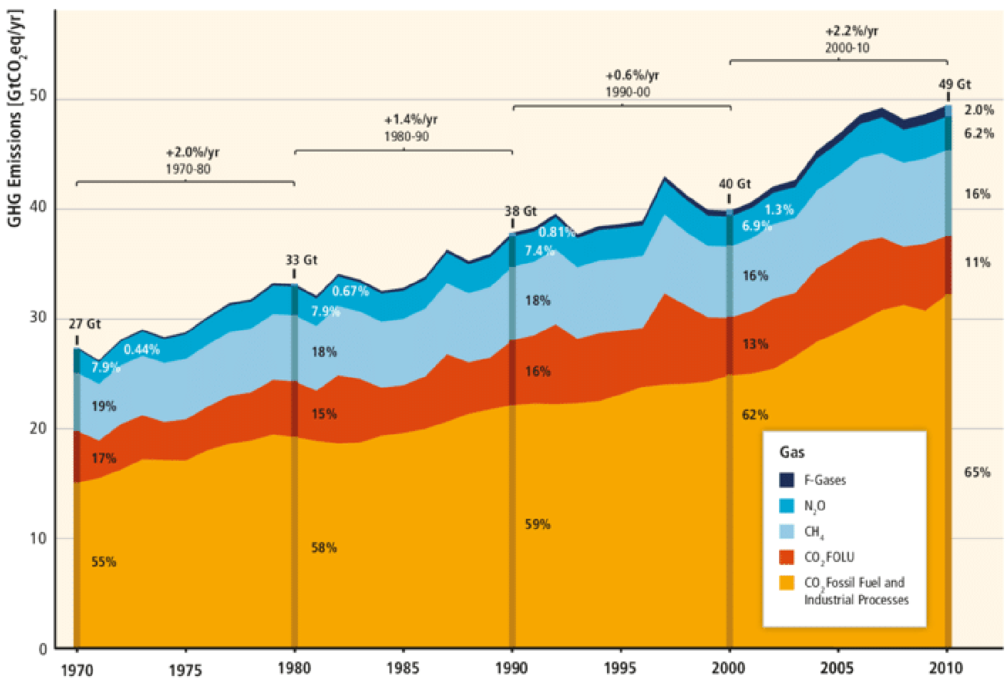

Figure 4 - Total annual anthropogenic GHG emissions by group of gases, 1970-2010. Source: IPCC, 2014.

Figure 4 confirms that the majority of total anthropogenic GHG emissions is made up by CO_2 emissions from fossil fuel combustion and industrial processes, and so it has been for the past 40 years. Moreover, the increase in the atmospheric concentration of CO_2 from 1750 has been the largest contributor to total radiative forcing (IPCC, 2013). For these reasons, after having ruled out natural GHG emissions from this study, from now on the attention will be focused only on CO_2 emissions and, more specifically, on CO_2 emissions from fossil fuel combustion, as it is their most relevant component, as has been highlighted above and further underlined from the graphic representation reported.

1.3. CO_2 emissions from fossil fuel combustion: world and regional trends

CO_2 emissions from fossil fuel combustion and industrial processes accounted for about 78% of the global increase in anthropogenic GHG emissions between 1970 and 2010 (IPCC, 2014). The growth of such emissions is ongoing, although at differing rates. In fact, in the 1970-2003 period, world growth rates were of about 1.6% per year on average, while in the period 2003-2011, the average annual growth rate spiked to 3.2%, mostly driven by China. Afterwards, these figures reduced to roughly the same entity of 1970-2003 between 2012 and 2014, with emissions even remaining constant in 2015. However, in the years between 2016 and 2018, growth rates have been progressively increasing, reaching 2% in 2018. This increase was owed to a new rise in global coal consumption that has been observed in 2017 and 2018, experiencing a 1.4% growth in the year 2018. The increase in CO_2 emissions of 2018, in general, can be reconducted to the fact that energy demand for this year has increased of 22 MJ, which were met, for one half, by relying on fossil fuels and, for the other half, on nuclear and renewables. In order to give, however, a more optimistic view on the matter, it should be pointed out that, between 2010 and 2018, the 15% increase in Total Primary Energy Supply (TPES) was met by decreasing the share of fossil fuels from 78.3% to 75.1%, and of nuclear from 4.6% to 3.9%, while, at the same time increasing the share of renewables from 17.1% to 20.9%.

When considering this evolution from the single countries' standpoint, however, further significant differences emerge. In fact, for a first level of analysis, the area graph in Figure 5 allows to make a comparison of fossil CO_2 emissions for OECD and non-OECD countries in the years between 1971 and 2017. Figure 5 shows that, while initially developed economies (i.e. OECD Countries) were the leaders in fuel combustion related CO_2 emissions, this role reversed after the beginning of the new Century. In this sense, non-OECD countries first equalled and then surpassed OECD countries' emissions of CO_2, that even experienced a decline in the last years considered in the graph.

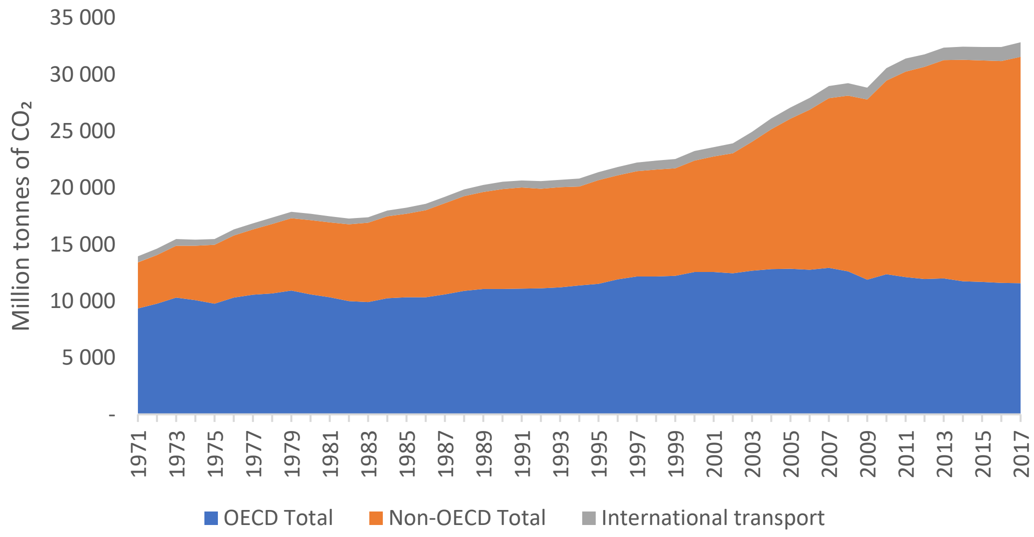

Figure 5 – Fossil fuel combustion related CO_2 emissions, OECD and non-OECD breakdown. Source: Author's own elaboration, based on IEA data (2019a).

However, among the various countries considered above, it makes sense to analyse on a standalone basis the top emitters' contribution to emissions, along with its evolution. Indeed, Figure 6, shows the million tons of fossil combustion-related CO_2 emissions in China[1], the US,

[1] From now onwards, by China it is meant People's Republic of China, excluding Hong Kong.

the OECD Europe[2] countries as a whole, India, and the Russian Federation, that are the five top emitters for the year 2018, with respective shares of 29.9%, 14%, 9%, 6.9%, and 4.6% (Olivier and Peters, 2020).

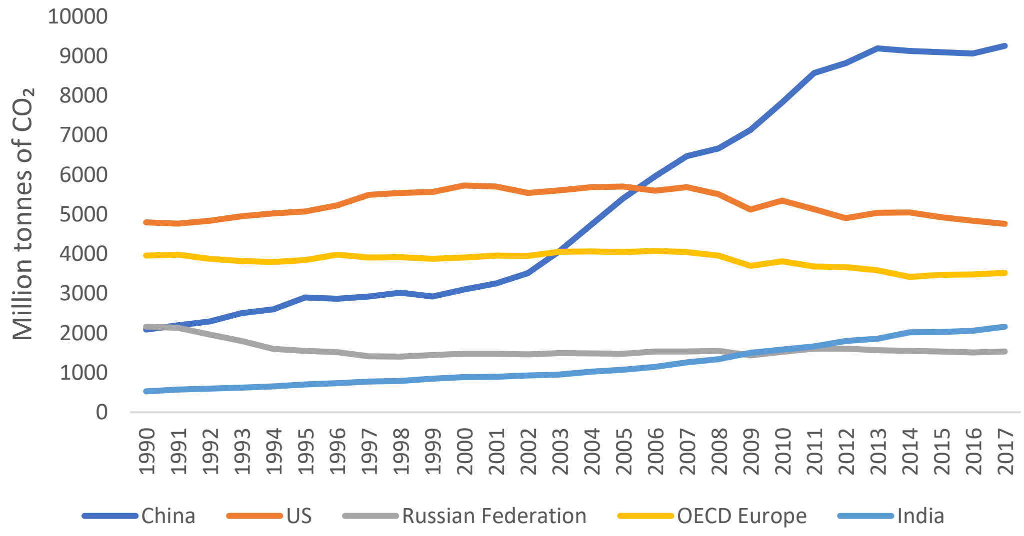

Figure 6 – Fossil fuel combustion related CO_2 emissions in top five emitting countries. Source: Author's own elaboration based on IEA data (2019a).

The steep increase experienced by China's CO_2 emissions is remarkable, such that, since 2006, it even surpassed the US as the world's largest emitter. However, it is important to note a decline in emissions experienced by China during the years 2014 through 2016, followed by a recovery in the last year of data considered. This event corresponded to an even greater decline in US emissions, which showed a 2.6% decrease in 2015, with this trend continuing up to the last year considered. On the other hand, the OECD Europe emissions, after falling in 2013 and 2014, started recovering in the following years, with emissions increasing by 0.9% in 2015. Just like China, India experienced a major increase in its CO_2 emissions, which is ongoing, as the rapid economic growth of this country continues. Lastly, the emissions of the Russian Federation have been quite stable after the huge drop caused by the Soviet Union's fall, but showed more recent declines since 2013, barely compensated by a slight recovery in 2017 (Olivier et al., 2016).

It is important to underline that the years of data studied in this graph, namely from 1990 to 2017, are going to be the time window used for the analysis carried out in the following Chapters of this work. This interval has been chosen as 1990 represents a benchmark year in a

[2] OECD Europe includes: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, and United Kingdom.

number of ways. In fact, on the one hand, it is the base year with respect to the Kyoto commitments for the majority of Annex I countries (UNFCCC, 2020). For this reason, it represents an important landmark when dealing with the study of CO_2 emissions, as countries consider this year's emissions to set their goals and measure their improvements to ensure their compliance with the Kyoto Protocol commitments. On the other hand, 1990 can be viewed as the year that, after the Berlin Wall had been demised in 1989, saw the beginnings of the process towards the market liberalization of the former Soviet Union's economies, which led to the establishment, among other things, of the Russian Federation in 1991. In this sense, 1990 can also be viewed as the year that shaped the world economy as it is known today, as the Central Eastern Europe countries moved from central planning economies to market ones. Furthermore, this economic transition brought to a huge reduction in emissions in those countries, which was linked to the contemporaneous output decline, but that proceeded even successively to the economic recovery (Chrimiciu and Dosi, 2011).

However, after pointing out the trends in the absolute CO_2 emissions, one further aspect should be brought to light. In fact, the roles of major contributors appear to be reversed when considering CO_2 emissions per capita, which are highlighted, for the same reference years and countries, in Figure 7.

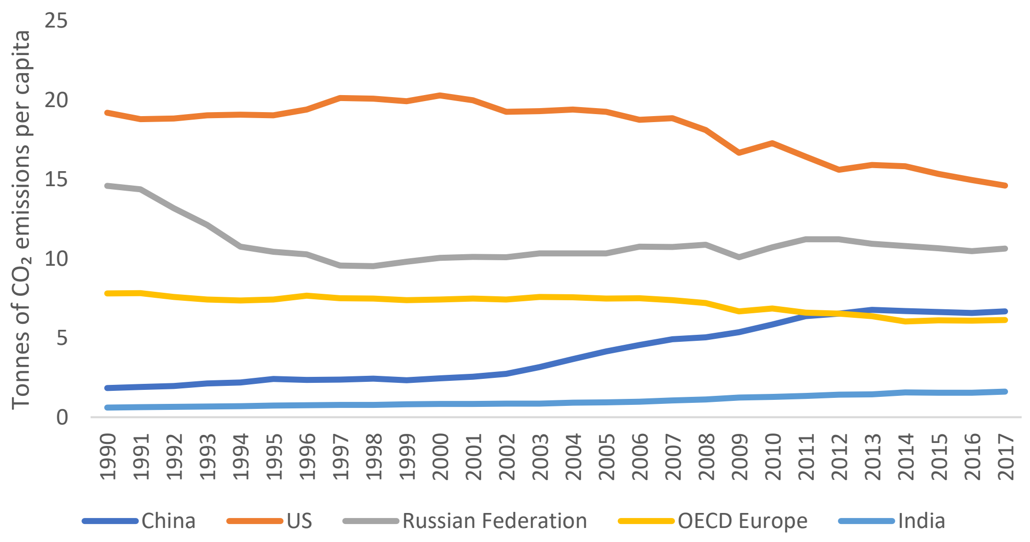

Figure 7 - Tonnes of CO_2 emissions per capita in the five top emitting countries. Source: Author's own elaboration based on IEA data (2019a).

By considering per-capita emissions, in fact, the US are the undiscussed leaders among the considered countries, even if they experienced an important reduction in the past 20 years. China, on the other hand, in this setting, currently ranks as the country with the third highest per-capita CO_2 emissions. Lastly, India shows the lowest numbers among the studied countries.

From these two simple representations, it is already evident how the analysis of different factors, such as the population of an economy, can shed a light on the drivers behind the amounts of emissions generated in one country. More specifically, there are four factors which contribute to the emissions' generation, namely population, GDP per capita, energy intensity, and carbon intensity (IPCC, 2014).

A first decomposition[3] of world fossil CO_2 emissions' change into these four factors for the years 1990-2017 is proposed in Figure 8. What stands out from the graph is that world's CO_2 emissions appear to have been increasing in all the considered years, with their percentage change being quite small in the last period considered, namely from 2013 to 2017, which are the years of recovery from the Great Recession.

The increase in emissions seems to have been mainly driven by economic and population growth in the last thirty years, with a substantial reduction of the economic driver experienced during the period 2008-2012. In the last period considered, however, economic growth has established a more important role as emission driver, whereas population growth's role has remained almost constant, as pointed out also by IPCC (2014). On the other hand, a factor that has been pulling back emissions is the energy intensity, namely the ratio between total primary energy supply and GDP, which will be object of a thorough analysis in Chapter 3. In fact, improvements in this ratio, which have been driven by technological advancements, changes in the economic structure and in energy mixes (IPCC, 2014), exerted a negative contribution to the growth in CO_2 emissions for all the considered periods, with a significant reduction in this role experienced during the crisis period, which seems to suggest a lower commitment to "energy efficiency" in periods of crisis.

Lastly, carbon intensity of energy, which is the ratio of CO_2 emissions over the total primary energy supply, went from being a negative contributor to emissions' growth in the period 1990-1999, to being a positive one in the years from 2000 to 2012, experiencing another shift in the sign of its contribution in the last period analysed, i.e. 2013-2017. The increase observed in the central periods has most likely been caused by an increased use of coal with respect to the other energy sources between 2000 and 2012 (IPCC, 2014).

[3] The decomposition operated in this Paragraph relies on the LMDI I method, developed by Ang et al. (1998), and Ang and Liu (2001). The change in CO_2 emissions is decomposed into four drivers (population, GDP per capita, energy intensity of GDP, carbon intensity of energy) according to the Kaya Identity. Both the LMDI I method and the Kaya identity will be presented in the next Chapter.

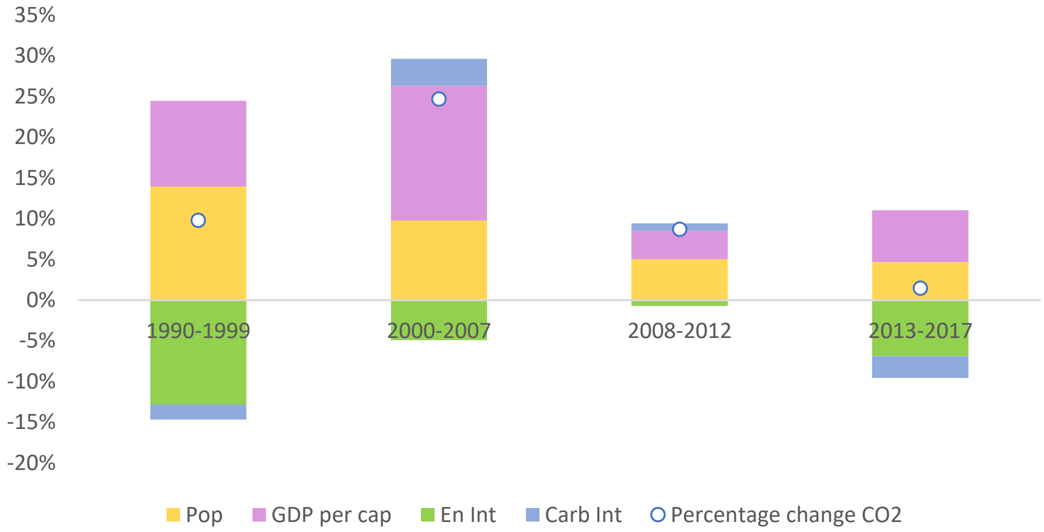

Figure 8- Decomposition of World's fossil CO_2 emissions, years 1990-2017. Source: Author's own elaboration based on IEA data (2019a).

This kind of decomposition of CO_2 emissions' change into its four determinants will be performed in the next Chapter for the major emitters outlined above, on a one by one basis, in order to get to the root of emissions' drivers in each of these countries, and analyse their single patterns and behaviours.

CHAPTER 2: A FIRST LEVEL OF DECOMPOSITION OF FOSSIL FUEL-CO_2 EMISSIONS

2.1. The Kaya Identity

When dealing with the topic of environmental degradation, it should always be accounted for the fact that three factors are strongly intertwined in the definition of any possible mitigation strategy, namely environment, economic development and energy. These have been appointed by Kaya (1997) as the three E's, underlying how, for instance, the energy provision by means of fossil-fuel combustion is economically viable, but is also directly connected with environmental issues, and, conversely, the reduction in the deployment of this kind of energy sources in order to improve environmental quality has clear repercussions on the economy, and on energy provision. In this sense, it behoves to set a formal link between these three variables.

To supply for that, one of the methods mostly deployed by the literature on this topic (see e.g. Albrecht et al., 2002; EBRD, 2011; Janssens-Maenhout et al., 2013; Tavakoli, 2017; Chen et al., 2018; Zheng et al., 2020) is the Kaya Identity, proposed by Yoichi Kaya at an IPCC seminar in 1989. The use of this identity allows to establish a link between energy-related CO_2 emissions, energy, economic activity and population in a certain area, for any moment in time. In this sense, the definition of such an equation, which is extremely simple from a mathematical standpoint, is a useful tool to proceed with the definition of the different components contributing to emissions. The mathematical link for a given country in a given year is defined as follows:

$$C = P \times \frac{GDP}{P} \times \frac{E}{GDP} \times \frac{C}{E}$$

Where: C are the energy-related CO_2 emissions, P is the population, GDP is the Gross Domestic Product, which can be computed using exchange rates or purchasing power parity, and E is the Total Primary Energy Supply. Given these definitions, the relation can be also seen as:

$$C = Population \times GDP\ per\ capita \times Energy\ Intensity\ of\ GDP \\ \times Carbon\ Intensity\ of\ Energy$$

That are the four quantities briefly explained at the end of the previous Chapter. In this sense, they can be seen as the "driving factors" of energy-related emissions, as they give an indication of the size of the country through the population, of its economic activity through the per-capita GDP, and of its carbon efficiency through energy intensity, which describes the amount of energy needed to produce a unit worth of economic output, and carbon intensity, which is the amount of CO_2 emitted per unit of energy used (Chirmiciu and Dosi, 2011; Tavakoli, 2017).

The use of the Kaya Identity has been widespread ever since its definition, as it presents a number of benefits. Firstly, being an identity, this measure does not carry any residual, and is extremely simple in its definition (Janssens-Maenhout et al., 2013; Tavakoli, 2017). Moreover, despite its simplicity, it still allows to make precise estimates of CO_2 emissions, as has been proven by Tavakoli (2017), who compared real emissions in 215 countries for a span of 20 years with estimations based on the Kaya Identity. From this comparison, it turned out that the latter could predict about 80% of the former, which is good considering that this equation is merely an accounting identity.

However, the extreme simplicity related to the use of this Identity comes at a cost. One example is the fact that it only provides a factual, ex post partition of energy-related emissions into its four drivers, without establishing their causes and their evolution (Janssens-Maenhout et al., 2013).

In order to fill in for this missing point, it is necessary to bring the analysis one step further, by means of decomposition techniques.

2.2. Decomposition analysis

2.2.1 Overview of the main techniques

Decomposition techniques are used to quantify the impact of several factors driving energy and emission changes. By decomposing a certain indicator in a given time span into its driving factors, in fact, it is possible to analyse each of these factors' role in the variation of the considered indicator (Caputo, 2012; Janssens-Maenhout et al., 2013).

Two main strands of techniques have been proposed by the literature, namely structural decomposition analysis (SDA) and index decomposition analysis (IDA) (Hoekstra and van der Bergh, 2003). The two methods have in common their fundamental aim of assessing the impact of several driving factors on a chosen indicator's change, with one main distinction: the former relies on the input-output model and data, whereas the latter relies on sector level data. IDA, by using aggregate sectoral data, entails less requirements in terms of data needed, which however leads to decompositions with a lower level of detail. Moreover, IDA allows to only assess direct effects, while SDA can also include indirect demand effects in its results. Lastly, the modelling framework used in the SDA is much more complex than the one requested by IDA, which however still provides a wide array of indicator forms, mathematical tools and indices.

For the analysis progressed in this work, more relevance has been given to wider country and time data availability and to feasibility, thereby privileging the use of IDA over SDA. As a matter of fact, some of previous works carrying out similar analyses to the one pursued in this work (see e.g. Metcalf, 2008; Chirmiciu and Dosi, 2011; Chen et al., 2013; Andreoni and Galmarini, 2016; Chen et al., 2018; Meng et al., 2018; Zheng et al., 2020) rely on IDA.

Indeed, the use of index decomposition analysis in the field of energy and environmental studies can be traced back to the late 1970s (Ang and Zhang, 2000; Ang, 2004). The surge of the world oil crises in 1973/74, in fact, led to increased questioning on the factors influencing energy demand and on its linkages with industrial production. From the deployment of the first simple decomposition techniques in those years, it turned out that the composition of industrial activity was not the only factor affecting energy demand, but that energy intensity also played a substantial role in this sense. However, after the late 1980s, a revision of these first, very intuitive techniques took place, leading to the use of more sophisticated methods, such as the arithmetic mean Divisia Index approach, introduced by Boyd et al. in 1987, and the Laspeyres index approach, formalized by Howarth et al. and Park in the first 1990s, although it had been already widely used in the majority of the literature since 1985. However, with the breakthrough works of, among the others, Ang and Liu (2003), Ang (2004; 2005) and Albrecht et al. (2002), these techniques have been gradually singled out in favour of "perfect decomposition techniques". This development led to a progressive convergence in the methodologies adopted, observed since the beginning of the new Century (Xu and Ang, 2013).

Given the popularity it had up to the first 2000s, it makes sense to firstly briefly focus on the Laspeyres index technique. This method derives from the Laspeyres price and quantity index largely used in economics. It relies on holding all the variables but the one considered constant at their base year values, while letting the other one freely change (Ang and Zhang, 2000; Ang, 2004). Formulae and further details related to this and the other methodologies reviewed in this Section can be found on APPENDIX A. The main advantage related to the Laspeyres index lays in its simplicity of use and understanding. This comes at a cost, however, since, by using this method, residuals arise, which can be so high at times as to make the analysis uninformative (Ang and Liu, 2007), as highlighted by numerical exercises performed by Albrecht et al. (2002). The same problem arose with the use of the technique of arithmetic mean Divisia index (AMDI), which deploys an arithmetic mean weight function. This method, in fact, although simpler in form than its other Divisia index counterparts, carries large residuals in some cases, like the one of cross-country decompositions with significant differences among the countries considered. Another drawback associated to this method is the fact that it fails when zero values are present in the dataset.

For these reasons, the rise of new index decomposition methodologies became crucial so as to develop more precise analyses, without the burden of large residuals hindering the utility of the decomposition task. In this sense, Ang (2004) defined the areas of evaluation for the different decomposition methodologies as their: "theoretical foundation, adaptability, ease of use, and ease of result interpretation". For the first of these areas, Ang and Zhang (2000), and Ang (2004) established several tests which allow to determine the degree of attractiveness of each IDA methodology:

- The ***factor-reversal test*** requires that, for the chosen method, in its multiplicative form, all contributing factors, when multiplied by each other, render the ratio describing the change of the variable considered, while, in its additive form, they all sum up to the change in the variable studied. This basically means that no residuals are present in the analysis, which implies a perfect decomposition, as the two sides of the equation perfectly equate.
- The ***time-reversal test*** requires the index number computed forward (i.e. from time 0 to time T) to be the reciprocal, in the case of multiplicative decomposition, or the opposite, in the case of additive decomposition, of that computed backward (i.e. from time T to time 0). This implies that the decomposition should give consistent results whether it is performed retrospectively or prospectively.
- The ***circular test*** requires that the index to be decomposed should also be obtained as the product, in case of multiplicative decomposition, or the sum, in the case of additive decomposition, of any intermediary, and complementary, decompositions (i.e. the decompositions from 0 to S and from S to T, with S being any point in time between 0 and T). This implies that the decomposed index is not affected by the way the indicator develops in the time span considered.
- The ***proportionality test*** requires that, whenever a driving factor is multiplied by a constant *k*, the new resulting index is also the *k*-uple of the initial one.

For what concerns the other areas, it is found that methods associated with a broader degree of adaptability to different decomposition problems, are clearly also more complex, therefore valuations should be performed before their application. The ease of use is, in fact, another criterion of choice for decomposition methods, and it closely relates to the facility with which a method can be applied to distinct problems. Lastly, the ease of result interpretation relates to the presence of residuals, which hinders results' understanding and the possibility to draw definite conclusions (Ang, 2004).

After having defined the main prerequisites to pick a good decomposition methodology for the problem considered, Ang and Liu (2003) and Ang (2004) move on to the description of some "perfect decomposition methodologies", that do not carry residuals in the analysis, satisfying the factor-reversal test. These are:

- Logarithmic Mean Divisia Index (**LMDI**) **I** and **II** methods. These methodologies use a log mean weight function. LMDI II has been the first perfect decomposition technique to have been implemented in the literature and was developed by Ang and Choi in 1997. LMDI I was subsequently proposed by Ang et al. in 1998 for the additive version, and by Ang and Liu (2001) for the multiplicative version. A further discussion on the LMDI I methodology will take place in the next Section.
- Mean rate-of-change index (**MRCI**) method. It was proposed by Chung and Rhee in 2001 and gets its name from the use of the "mean rate-of-change index" for weighting the terms of the decomposition. It is only available in additive form, and its formulae are less straightforward than the ones of the first two methodologies.
- **Fisher Ideal index** method. It has been proposed in 2002 by Ang et al. as a reformulation of the Laspeyres index which yields perfect decomposition, and further developed by Ang and Liu in 2003, and Boyd and Root in 2004. It is available only in multiplicative form. A further insight on this methodology will be provided in the next Section.
- **Shapley/Sun** method. This term refers to two methodologies proposed, respectively, by Albrecht et al. (2002) and by Sun (1998), which have been deemed as equivalent in their mathematical results by Ang and Liu (2003). These methodologies rely on a distribution of the residual term from the traditional Laspeyres index method among the different driving factors, based on the "jointly created and equally distributed principle" (Albrecht et al., 2002) for Sun, and on the axioms of symmetry, no inessential players and additivity for the method proposed by Albrecht et al., based on the Shapley value's theoretical framework. By doing so, the two decomposition techniques essential yield the same result. The advantages related to these methodologies are, other than the fact that they perform perfect decomposition, the symmetry of their decomposition, meaning that all the factors involved are treated in an impartial fashion, and the possibility to perform complex decomposition tasks. However, this means that formulae connected to

these methodologies can become quite cumbersome, especially with a large number of factors involved in the decomposition, which is the case of most decompositions in the energy and environmental field.

2.2.2 LMDI I and Fisher Ideal index methods

This paragraph focuses on the two techniques of LMDI I and Fisher Ideal index decomposition, briefly reviewing their advantages and shortcomings. Given that these two methodologies have been chosen over other perfect decomposition techniques in tasks similar to the one performed in this work (see e.g. Metcalf, 2008 and Chirmiciu and Dosi, 2011 for the Fisher Ideal index method; and Chen et al., 2013; Andreoni and Galmarini, 2016; Chen et al., 2018; Meng et al., 2018 and Zheng et al., 2020 for the LMDI I method), they have been chosen as the techniques that are going to be applied in this study.

The LMDI I method, as previously mentioned, relies on the use of a log mean weight function. This allows to obtain much better results than its forerunner AMDI. In fact, LMDI I method does not leave any residuals, and is not subject to the zero-values problem which affects AMDI as, when zero values are replaced by small positive numbers, results converge, thereby solving all the main issues related to AMDI (Ang, 2004). Another feature of LMDI I that made it superior to the LMDI II method as well, was highlighted by Ang and Liu (2001) when introducing it for the first time in its multiplicative form and is its consistency in aggregation. This means that, whether by computing it in more steps or in a single step, the index decomposition returns the same results. This feature is particularly relevant considering that often decompositions are performed at more disaggregation levels (e.g. by country, by industrial sector, or by fuel type). Furthermore, the LMDI I method passes all the tests mentioned above but the proportionality test (Ang et al., 2004). A possible shortcoming of this method is that it is not robust to negative values, given the properties of logarithmic function. However, given that in energy and environmental studies negative data are extremely rare, this issue should not be too relevant. Lastly, Albrecht et al. (2002) pointed out that the use of the log mean weight function implies an assumption of constant growth rates, and a normalization of the weight function, since the sum of all weights is actually slightly less than one. Despite these flaws, the LMDI I method is currently the most widely deployed technique, as it delivers perfect decomposition, without requiring cumbersome computations. In this and the following Chapter, this methodology will be used, in its additive form, to perform decompositions for the change in energy-related CO_2 emissions, and in industrial energy consumption, respectively, in the countries targeted in Chapter 1 as the major emitters. The mathematical formulation for the LMDI I method can be found in APPENDIX A.

The Fisher Ideal index method relies on an extension of the conventional Laspeyres and Paasche indices. The Paasche index is very similar to the Laspeyres, but with the main difference that, while Laspeyres is based on a prospective reasoning, Paasche uses a retrospective view (Albrecht et al., 2002). Computing the geometric mean of those two indices, the Fisher Ideal index is obtained (Ang et al., 2004; Metcalf, 2008). This method overcomes the issue of residuals' presence which arises when using the two indices on a standalone basis, thereby performing a perfect decomposition. In addition to that, it passes all the tests mentioned above, and it is also robust to negative values. However, it appears not to be consistent in aggregation, and its formulae can be very complicated when dealing with a large number of factors (Ang et al., 2004). In the following Chapter, this methodology will be used to perform decompositions for energy intensity's change in the countries targeted in Chapter 1 as the major emitters. The mathematical formulation for the Fisher Ideal index method can be found in APPENDIX A.

2.3. An application of LMDI I to fossil fuel CO_2 emissions

2.3.1 Data and framework

Throughout Section 2.3, a decomposition of the change in CO_2 emissions from fossil fuel combustion is operated for China, the US, the Russian Federation, India, and three representative countries of the OECD-Europe, i.e., Germany, the UK and Italy.[4] This is owed to the fact that Germany represents Europe's most important economy, and, as such, a benchmark for the rest of the European economies. As a consequence, it is also the European country which emits more in terms of total GHGs (Eurostat, 2020). The UK, on the other hand, is the second largest EU emitter, and, since 1990, has undergone a significant process of decarbonization and a structural shift, which is of peculiar interest for this kind of analysis. Lastly, Italy, that ranks as the fourth largest EU emitter, has been chosen to analyse the national situation, and also for the sake of comparison, given that the third largest EU emitter, France, relies on a completely different fuel mix, given its large reliance on nuclear. For what concerns the other countries selected, they are the largest world emitters, and represent interesting objects of analysis for the differing driving forces of their emissions. In fact, while the US has been the

[4] Detailed results of the decomposition can be found in Appendix B (Table B.1).

largest emitter for the first half of the study period, China surpassed it owing to its growing economy, and to the use of a more carbon-intensive fuel mix. On the other hand, European emissions are on a declining path, also because of an increased regulatory concern on the matter. Of opposite direction are the emissions produced from India, where the economic and demographic drivers are particularly relevant. Lastly, the Russian Federation also represents a case of interest, as it had to endure a severe drop in its economy and undergo a recovery process that would prevent a spike in emissions.

After providing an overview of the countries that are object of the decomposition analysis which will be performed, it makes sense to review the time window considered as well. As stated in the previous Chapter, the time span analysed ranges from 1990 to 2017. However, a further subdivision will take place in this decomposition analysis, in order to form four sub-periods. These will be:

- ***1990-1999*** is the first decade of data analysed, starting from the Kyoto protocol base year, and following the fall of the Soviet Union.
- ***2000-2007*** is the pre-crisis period, during which China fully experienced its economic transition, symbolized by its entry into the World Trade Organization in December 2001 (WTO, 2020).
- ***2008-2012*** is the recession period. During these years, the world's major economies have been hit, first by the financial and economic downturn of 2008-2009, that saw its beginnings in the US, but spread worldwide, and then by the European sovereign debt crisis of 2010-2012.
- ***2013-2017*** is the recovery period, allowing to establish the effects of the crises on emissions, and on the way their major drivers' roles may have changed.

Another remark must be made concerning the choice of the GDP measure adopted. In order to provide a better comparison among the different countries, without accounting for inflation issues which may have arisen during the period considered, GDP at constant 2015 prices, expressed, using exchange rates, in US dollars (USD) was used. This is also what has been done by Chen et al. (2013), Andreoni and Galmarini (2016), Zheng et al. (2020), who preferred the use of GDP at constant prices computed using exchange rates over GDP computed using purchasing power parity, which would have given more weight to emerging economies, resulting in smaller wealth disparities (Raupach et al., 2007). The GDP data for this work have been retrieved from the United Nations Statistics Division database (2019). On the other hand, the data on fossil fuel related emissions, expressed in million tonnes of CO_2, population, expressed in millions, and total primary energy supply, expressed in Petajoules (PJ)[5] equivalent, have been provided by the International Environmental Agency's report on CO_2 emissions from fuel combustion (IEA, 2019a), which covers world and regional data from 1971 to 2017.

2.3.2 Germany, United Kingdom and Italy

At the EU level, the commitments to reduce emissions, by increasing the use of renewables and fostering energy efficiency, are enclosed in a number of regulations and policy initiatives. Some of the most remarkable ones are the EU- Emissions Trading System (ETS), which is a cap-and-trade scheme, creating a uniform price for emission allowances in the covered sectors, that account for 45% of Europe's total GHG emissions (Kisielewicz et al., 2016); the Effort Sharing Decision (ESD), for those sectors which are not covered by the EU-ETS, which requires to meet 2020 targets on GHG emissions, set for each Member State with respect to their 2005 base year-levels; the Renewable Energy Directive (RED), that sets a 2020 target for each Member State in terms of the percentage of renewable energy sources over the gross final energy consumption; and the Energy Efficiency Directive (EED) which requires Member States to fix indicative targets relatively to their gross primary energy consumption (EEA, 2017).

Germany

Germany is Europe's leading economy, and, as such, it is also its leading emitter, with, as of 2018, a 23% share on the overall EU-27 GHG emissions (Eurostat, 2020). Despite this, Germany's fossil CO_2 emissions have been on a declining path for the whole time window considered, with a total 23.5% decrease, going from about 940 million tons in 1990 to about 719 in 2017.

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for Germany is proposed in Figure 9.

[5] 1 Petajoule = 10^{15} Joules.

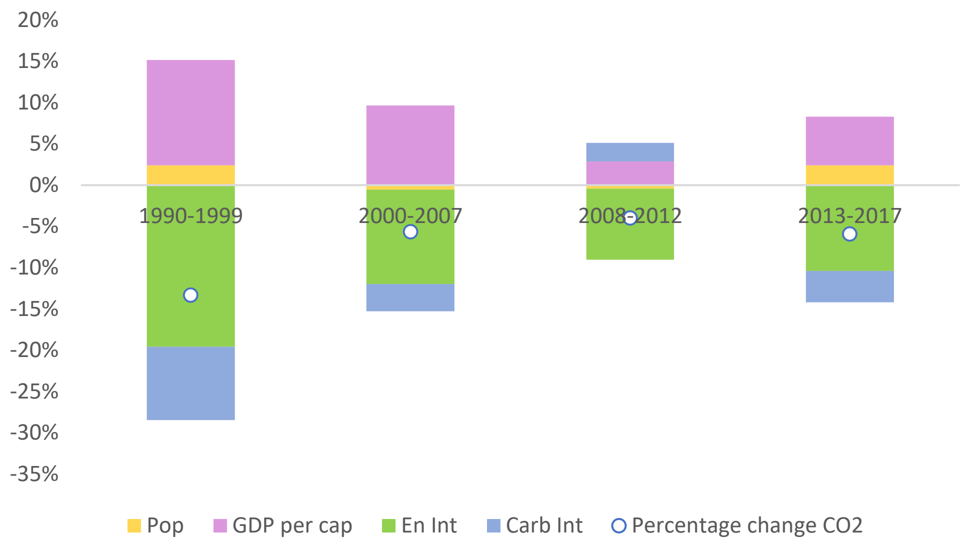

Figure 9 - Germany's fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

Figure 9 shows declining emissions are obtained for all four subperiods.

For what concerns the drivers of emissions, Figure 9 shows that the ***energy intensity of GDP*** is the main factor causing the emissions' decline. In fact, in the absence of any reduction experienced by this driver, and with all other factors remaining equal, emissions would have increased by 7%, 5%, 5%, 4%, respectively, in 1990-1999, 2000-2007, 2008-2012, 2013-2017. In this case, the decline in energy intensity, as will be explained in further detail in the following Chapter, is to be imputed more to an efficiency improvement across sectors, rather than to a structural change.

Another factor whose contribution sign remained consistent throughout the four subperiods is the ***GDP per capita***. In fact, the contribution of this factor has remained positive for the whole period, even during the crisis subperiod, namely 2008-2012, where it merely experienced a decline in its positive contribution, which went down to 3%, from the 10% of 2000-2007 (i.e. without the increase in GDP per capita experienced in the same subperiod, and with all other things equal, emissions would have been 3% lower).

The last two driving factors experienced a sign change in their contribution to the emissions' variation across the studied subperiods.

The ***population*** driver, in fact, had a small negative contribution to the change in emissions in the central subperiods, namely 2000-2007 and 2008-2012, whereas it positively contributed to the change in emissions in the first and last subperiods, namely 1990-1999 and 2013-2017. This is because, indeed, population in Germany declined in the central periods, while it increased in the two extremes. Given that an increase in the population positively correlates with emissions, the sign of the change in population is coherent with its contribution to emissions' variation.

Lastly, the ***carbon intensity of energy*** driver exerted a negative impact on the emissions' change in all subperiods but the crisis one (i.e. 2008-2012). This factor is particularly relevant for the study of Germany, as it is the largest coal consuming country in the European Union, totalling, in 2015, a production of brown and hard coal of more than 5 Exajoules[6] (EJ), and a net import of almost 2 EJ (Olivier et al., 2016). In particular, coal production experienced an increase between 2008 and 2012, which may explain the change in the contribution sign of the carbon intensity of energy experienced in this period, to then decline after 2012, counterbalanced however by an increase in the net imports of coal. Nevertheless, in the last years Germany decreased its consumption of coal, with a 7.2% reduction observed only in the year 2018, oil, and natural gas (Olivier and Peters, 2020). This was made possible by an increased reliance on renewables, which will be addressed in the next Chapter.

United Kingdom

The United Kingdom (UK) is the second largest emitter among the European countries, with its 2018 GHG emissions being a 12.8% share on the EU-27 total for the same year.[7] Indeed, the UK once was the largest European emitter, due to the massive economic development it experienced during the 18th and 19th century Industrial Revolution. However, this major development resulted in an equally as important environmental damage, which prompted the UK to set regulations early on, with the first ones being the Clean Air Acts of 1956 and 1968 (Agbugba, 2019). Successive regulations include the Climate Change Act of 2008, which acknowledged the UK's commitments to reduce its impact on the self-titled phaenomenon. All these efforts ensured that, in the time window considered in this study, UK's CO_2 emissions diminished, with 2017 figures being only about 65% of the 1990 base-year levels.

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for the UK is proposed in Figure 10.

[6] 1 Exajoule = 10^{18} Joules.
[7] The EU-27 total excludes UK's emissions.

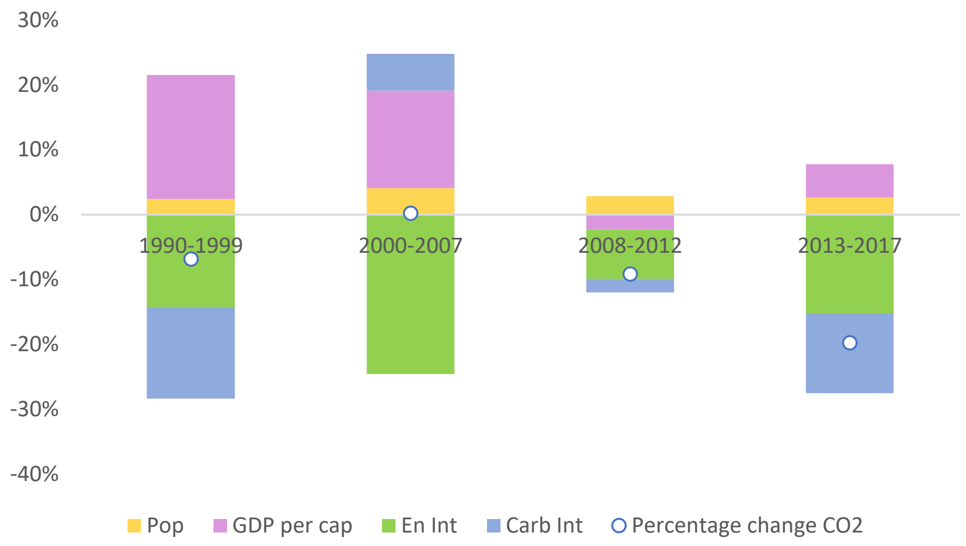

Figure 10 - UK's fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

UK's CO_2 emissions have been declining in all subperiods but the 2000-2007 one, when they experienced a mild 0.22% increase.

Among the considered drivers, two maintained the same sign of their contribution to the change in emissions throughout the four subperiods.

The first is the ***energy intensity of GDP*** driver, whose contribution has remained steadily negative for the four subperiods. In fact, in the absence of any change in this driver, and with everything else equal, UK's emissions would have been 14%, 25%, 8% and 15% higher, respectively, in the 1990-1999, 2000-2007, 2008-2012 and 2013-2017 subperiods. In this case, as will be further explored in the following Chapter, the ongoing structural change in UK's economy is as important a driver as the improvement in its overall energy efficiency, owing to its transformation from an economy centred on pollution-intensive manufacturing sectors to a more service-based one.

The other driver whose sign remained the same throughout the four periods, although opposite to the one of energy intensity, is the ***population***. In fact, the contribution of this driver on the change in emissions has remained positive in all the four subperiods, as population increased consistently throughout the full time window considered.

The ***GDP per capita*** driver, however, did change the sign of its contribution across the four subperiods. In fact, its contribution to the change in emissions is positive for all the subperiods, but the crisis one (i.e. 2008-2012). The reason behind this sign change appears to be pretty straightforward, as the Great Recession adversely impacted on UK's GDP per capita, with

British economy in 2009 being 5.5% below its peak in the first quarter of 2008 (Vaitilingam, 2009), and with this trend continuing up to 2012, when the economy finally started to recover, as highlighted by the sign change experienced in the last subperiod considered, namely 2013-2017.

Lastly, the ***carbon intensity of energy*** driver exerted a negative contribution in all subperiods, but the 2000-2007 one. This temporary sign change may be owed to an increased consumption of fossil fuels, mainly coal, experienced by the UK precisely in those years, which were later outpaced by an increased consumption of renewables, starting from 2004 (Agbugba, 2019). Given that the UK is the sixth largest coal consuming country in the EU (Olivier et al., 2016), this country's lower reliance on coal has relevant consequences at the EU level.

Italy

Italy is the fourth largest EU emitter, accounting, in 2018, for a 11.3% share of total EU-27 GHG emissions (Eurostat, 2020). Concerning the time window considered in this study, Italian CO_2 emissions have increased for the first half of the full sample period, from 1990 to 2005, to then decline in the second half on a steady path, except for the two years 2010 and 2015, which showed isolated increases with respect to their preceding years (IEA, 2019a).

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for Italy is proposed in Figure 11.

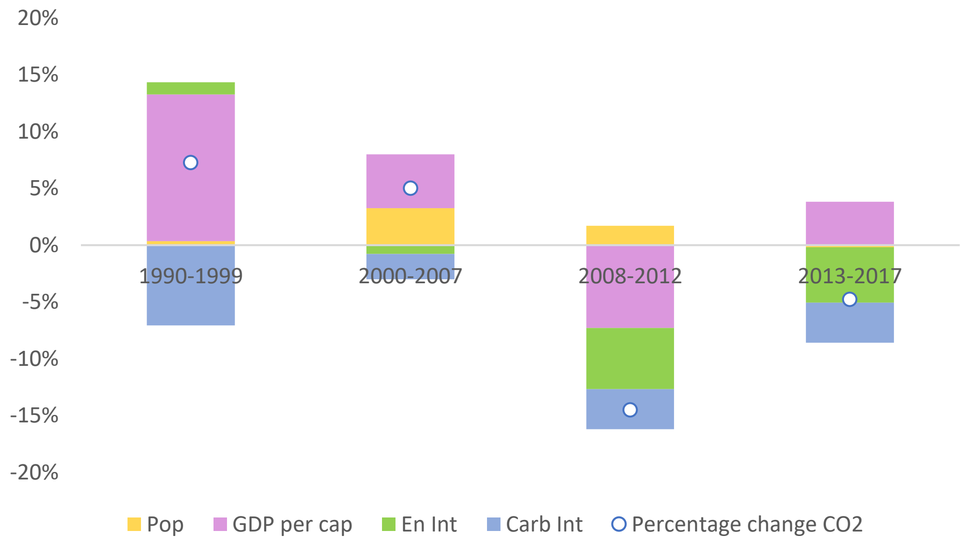

Figure 11 - Italy's fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

The two opposite trends in Italian CO_2 emissions are highlighted by the subperiod decomposition, with the first two being characterized by an increase in emissions, and the last two by a decrease.

For what regards the driving factors, only one of them exhibits sign consistency in its contribution, namely the ***carbon intensity of energy*** driver. This driver, in fact, had a negative impact on the emissions' change throughout the four subperiods analysed. This constant reduction in the carbon intensity of energy experienced in Italy is owed to its declining reliance on oil and coal, compensated by an increasing reliance on renewable energy sources and other low-carbon fuels (Caputo, 2012), such as natural gas, whose consumption however decreased by 3.3% in 2018 (Olivier and Peters, 2020). Furthermore, in the first two subperiods, this factor had a primary role in the reduction of emissions, with a relevance even greater than the one of the ***energy intensity of GDP*** driver, which, unlike with the other two EU countries analysed, unexpectedly exerted a positive impact on the emissions' change in the first subperiod. However, in all the following subperiods, the contribution of the energy intensity of GDP has become negative, reflecting improvements mainly on the side of the economic structure of Italy, which will be addressed in more detail in the following Chapter.

The ***population*** driver has a positive contribution in all the subperiods but the last one, when it exhibited a negative impact on the emissions' variation, as a consequence of Italian population declining since 2014 (Balmer, 2020).

Lastly, the ***GDP per capita*** driver exerted a positive pressure on the emissions' change in all subperiods but the crisis one (i.e. 2008-2012). This is because, indeed, Italy suffered severe consequences on its economy from the Great Recession and from the sovereign debt crisis, causing a recession which stretched out from 2008 to 2014, worsening even more an economic situation which was already unstable and weak (Di Quirico, 2010). Indeed, between 2000 and 2012, Italy has been one of the world's worst performing countries in terms of GDP creation (Andreoni and Galmarini, 2016). On the bright side, economic recovery started from 2014, and proceeded until the last year of data analysed, which nevertheless shows a GDP per capita value which is still lower than the peak value experienced in 2007, and much lower than the Germany and UK's corresponding values.

2.3.3 United States

The United States (US) are the World's second largest emitters, totalling about 4,761 million tons of CO_2 emissions in 2017, which is only 0.87% lower than its 1990 value (IEA, 2019a). US' emissions are currently on a declining path, which began shortly after the beginning of the new Century. The US' commitment towards emissions' reductions is sealed by the adoption of several regulations, such as the Clean Air Act, amended in 1990, which includes the setting of policies aiming to improve pollution standards and the promotion of more efficient technologies (Andreoni and Galmarini, 2016). Nevertheless, US emissions still represent an approximate 14% share[8] of world's total CO_2 emissions, with their total emissions in 2017 being almost three times as much as the sum of those of the same year for the three EU countries presented in the previous Section together, or more than those of the Russian Federation and India put together.

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for the US is proposed in Figure 12.

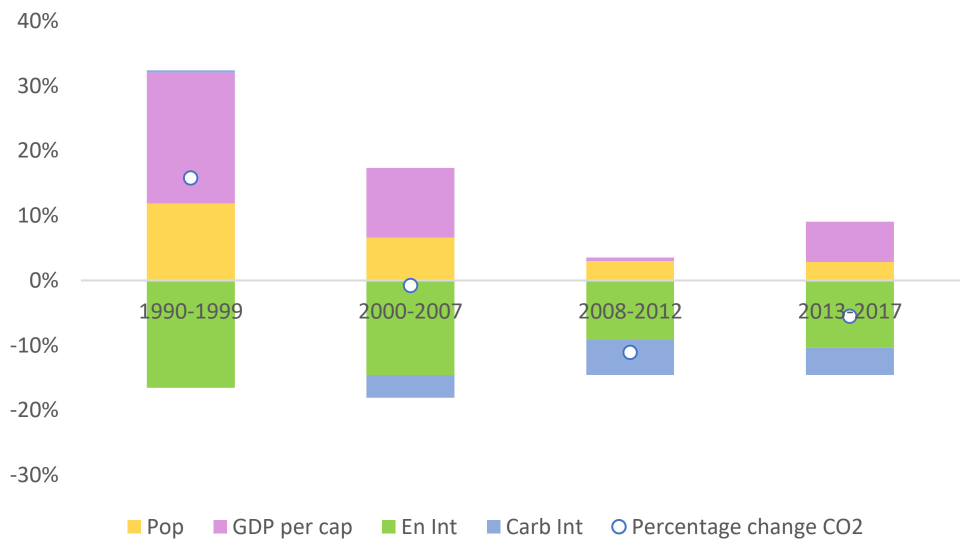

Figure 12 - US' fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

Exception made for the first subperiod, when they increased by 16%, US CO_2 emissions have been on a declining path, reaching bottom figures in the crisis subperiod, 2008-2012, when emissions decreased by 11%.

Relatively to the drivers, it can be noted that they all have a consistent contribution sign throughout the four subperiods, except for the ***carbon intensity of energy*** that, after exhibiting

[8] Number based on Author's computations from IEA data relative to fossil CO_2 emissions in 2017 (IEA, 2019a).

a small positive contribution to the change in emissions in the first subperiod, changed its contribution sign for the remainder of the periods. This is because the US are indeed improving their fuel mix, by reducing their reliance on coal, compensated for, however, by an increased use of natural gas and oil. Another important compensating role, in this sense, is played by renewable and nuclear sources, which, together, accounted for 36% of 2018 power generation in the US, and for 21% of the Total Primary Energy Supply (TPES) for the same year. Despite these efforts, the US still had, in 2018, a 79% share of their TPES provided by fossil fuels (Olivier and Peters, 2020).

Next, the main driver fostering emissions' reduction is the ***energy intensity of GDP***, whose contribution is particularly relevant. In fact, in the absence of any improvement in the energy intensity ratio, and with everything else remaining equal, emissions would have increased by 33%, 14%, and 4%, respectively, in the subperiods 1990-1999, 2000-2007 and 2013-2017, whereas they would have decreased only 2% in the subperiod 2008-2012, as opposed to the actual 11% decline experienced. This continuous improvement in energy intensity, which slowed down only during the crisis subperiod, is to impute mainly to sectoral energy efficiency, as will be seen in more detail in the following Chapter.

On the side of the positive contribution to emissions' variation, the most important role, exception made for the crisis subperiod of 2008-2012, when it contributed only 1% to the change in emissions, is covered by the ***GDP per capita*** driver. Indeed, during the crisis subperiod, GDP per capita, after experiencing an important drop in 2008 and 2009, bounced back up already in 2010, reaching a value as high as it was in 2007 in 2014. This resulted in a contribution to emissions' variation of this driver which is still positive, although not so relevant, even in the Great Recession's subperiod.

Lastly, the ***population*** driver always exerted a positive contribution to the change in emissions, as a consequence of increasing population throughout the entire period analysed.

2.3.4 China

China is currently the world's largest emitter of fossil CO_2, with a share of about 28% over the world's total emissions.[9] This leading role saw its beginnings in 2006 and, afterwards, China alone contributed 64.8% to the global increase in emissions during the period 2007-2012 (Meng

[9] Number based on Author's computations from IEA data relative to fossil CO_2 emissions in 2017 (IEA, 2019a).

et al., 2018). Moreover, in 2013, China's per capita emissions surpassed those of the OECD Europe.

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for China is proposed in Figure 13.

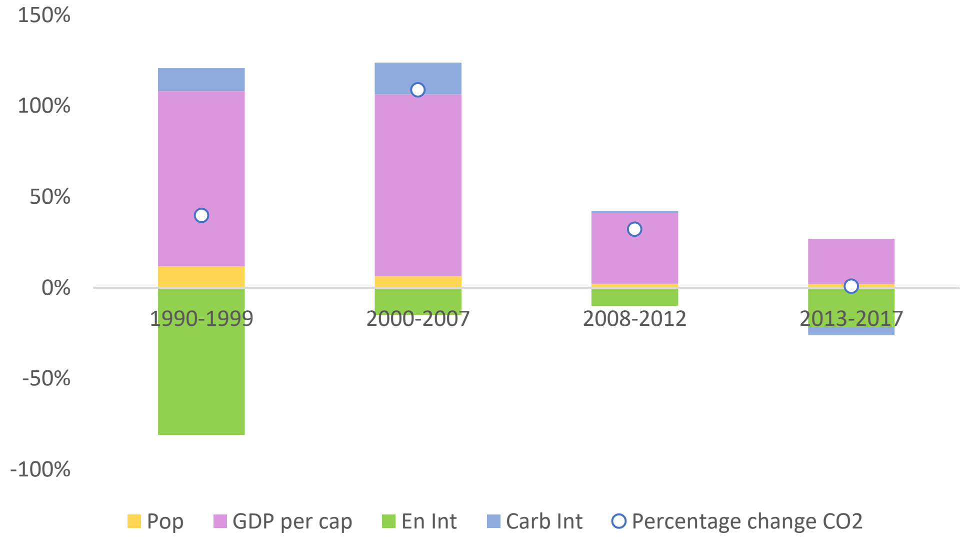

Figure 13 - China's fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

Figure 13 shows that China's emissions have increased in all the considered subperiods, reaching a 109% growth during the second one. However, the last subperiod considered, namely 2013-2017, shows a mere 1% increase, pinpointing a phase of stabilization and commitments towards emissions' reduction labelled by Zheng et al. (2019) as "the new normal".

As for the drivers of the change in emissions, it can be noted that almost all the increase in emissions is to be ascribed to an increase in the Chinese economy, represented by the ***GDP per capita*** driver. In fact, in the absence of the increase experienced by this driver, and with everything else remaining equal, China's emissions would have diminished by 56%, 7% and 24%, respectively, in the subperiods 1990-1999, 2008-2012 and 2013-2017, while they would have increased only by 9%, as opposed to 109%, in the subperiod 2000-2007. Indeed, China's economic development has been massive in the time window considered, especially after its accession to the World Trade Organization in 2001. This rapid economic development has mainly been driven by "the production and consumption of high-energy-consuming and high-carbon-emitting products" (Zheng et al., 2019), causing a major increase in emissions produced by this country, whose economy appeared to be driven mainly by heavy and polluting industries. However, with increasing environmental concern worldwide, China could no longer continue with this emissions-filled growth path. For this reason, China adopted regulations and policies to mitigate environmental damages, such as its 12th Five-Year-Plan of 2011 on Energy Saving and Emission Reduction, and its 13th Five-Year-Plan for economic development of 2016, which advocates for a more sustainable and inclusive growth (Meng et al., 2018). Furthermore, it also ratified the Paris Agreement in 2015, which requires the achievement of emissions' reduction, and to peak emissions to the latest by 2030 (Climate Action Tracker, 2019). Due to these commitments, other than an ongoing sectoral energy efficiencies' improvement, which will be addressed in the next Chapter, China is said to have entered a "new normal" phase in its development, because of its continued economic growth, but accompanied by a much lower emissions' growth, symbolized by the 1% increase in fossil CO_2 emissions in the subperiod 2013-2017, which corresponded to a 31% growth in GDP[10] in the same period.

For what concerns the other drivers in China's fossil CO_2 emissions' change, there are further interesting insights to be examined.

First, the relevance of the ***population*** driver, which already had a relatively small role in the increase of emissions in the first subperiod (i.e. in the absence of population growth, emissions would have been 12% lower in the subperiod 1990-1999), declined even more in the following subperiods, down to 2% in the 2013-2017 subperiod. This contained growth, which however still means that there has been an approximate additional 200 million people in the full time window considered, on top of the important population base China had in 1990 (about 1135 million), is to be imputed to the implementation, since 1978, of the family planning policy (Chen et al., 2013; Zheng et al., 2020), which has been relaxed to a "two-children policy" in 2016. Given that additional population means additional demand and consumption, other than an improved urbanization rate, the effect of the population driver on the emissions' change is positive in all subperiods considered, correspondingly to an increase in population which occurred at the same time.

Another factor whose role changed throughout the years is the ***carbon intensity of energy***. In fact, this variable positively contributed, to differing extents, to the increase in emissions in the subperiods 1990-1999, 2000-2007 and 2008-2012 whereas, in the last subperiod, namely 2013-2017, its contribution became negative. This is because the majority of primary energy consumption in China was, and still is, represented by coal, that accounted for the 59% in 2018 (Zheng et al., 2020). In fact, despite the efforts towards a "greening" of China's economy, the country's resilience on coal is still strong. On a silver lining, however, China is increasing its reliance on other energy sources, such as renewables, with hydropower making up 19.5% of

[10] Growth rate computed for the GDP at constant prices, in 2015 USD, using UN Stats database (2019).

the country's energy generation in 2015, and wind and solar altogether accounting for 5% in the same year (Olivier et al., 2016), but mostly oil, whose consumption increased by 5% in 2018, and natural gas, whose consumption experienced a 17.7% increase in the same year (Olivier and Peters, 2020).

Lastly, ***energy intensity of GDP*** appears to be the most relevant negative driver influencing the emissions' variation. This variable, in fact, exerted a negative contribution against the emissions' increase for all the subperiods considered, with the highest experienced in the first and last subperiods (i.e. 1990-1999 and 2013-2017). This decrease has been driven by a number of variables, including technological progress, energy structure, and structural shift (Chen et al., 2013). In the next Chapter, the contributions of two of these factors to the decrease in energy intensity, namely sectoral energy intensity and structural effect, will be addressed in more detail.

2.3.5 India

In 2017, India contributed about 6.6% to global fossil CO_2 emissions[11], a share which has already increased to 6.9% in 2018 (Olivier and Peters, 2020). Considering that, at the beginning of the study period, this share was only 3.8%, it can be noted just how fast and to what extent the emissions produced by this country have increased in the past 30 years, causing it to even surpass, in 2009, the ones of the Russian Federation and rank as the fourth largest emitter in the World.

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for India is proposed in Figure 14.

[11] Number based on Author's computations from IEA data relative to fossil CO_2 emissions in 2017 (IEA, 2019a).

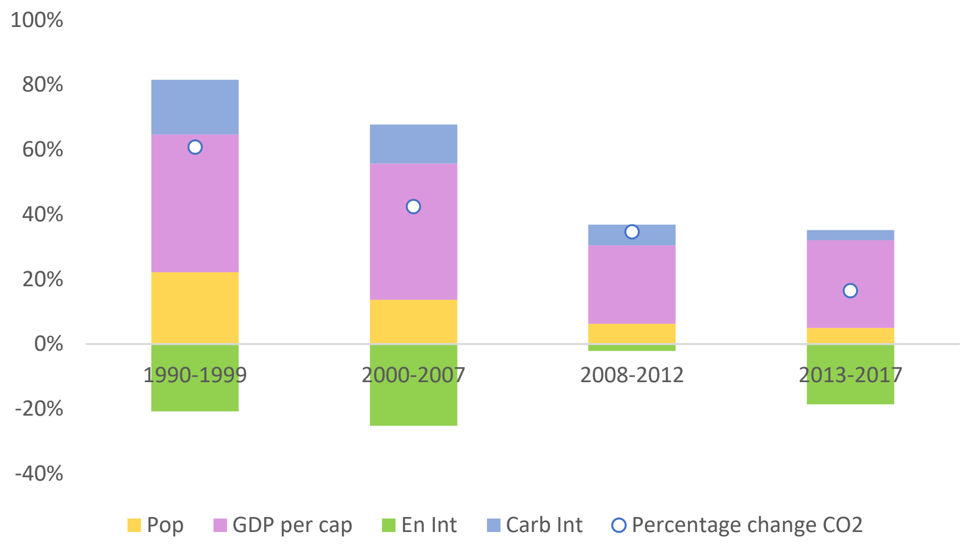

Figure 14 - India's fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

India's fossil CO_2 emissions increased, even if at declining rates, in all the considered subperiods.

For what concerns the driving factors, the Indian situation presents some similarities to the situations of the countries studied up to this point.

Indeed, just like Germany, the US and China, the ***GDP per capita*** driver exerts a positive contribution to the emissions' increase, with its contribution being at its minimum in the 2008-2012 subperiod, but still meaning that, in that subperiod, in the absence of any change in the GDP per capita, and with all the rest remaining equal, emissions would have increased by 11%, as opposed to the observed 35% increase. This is owed to the huge development experienced by the Indian economy, with the annual growth of GDP being around 7% for more than a decade (Olivier and Peters, 2020). This made it such that the economic driver resulted as the most relevant driver of emissions' change in the decomposition analysis reported. Moreover, according to the decomposition analysis performed by Andreoni and Galmarini (2016), the increasing relevance of this country in the international production system for the period 2004-2008 was another significant driver of the increased emissions experienced by this country in the same period.

Another factor that thus far generally exerted a negative role in affecting the change in emissions, namely the ***energy intensity of GDP*** driver, maintains the same role also in the Indian situation. In this case, unlike what happened with China, the experienced decrease in the energy intensity of GDP is owed in its entirety to improvements in sectoral efficiency, whereas the economic structure of India had a negative impact on this driver.

An especially relevant role in the Indian case is played by the ***population*** driver. In fact, the positive contribution exerted by this factor on the emissions' increase, linked to the continuous expansion of the Indian population, is relatively greater than in any of the countries previously observed, reaching its peak in the first subperiod, with a 22% contribution. Indeed, India is set, according to the United Nations World Population Prospects (2019) to surpass China as the world's most populous country by 2027. Despite the fact that the growth in its population is ongoing, India is managing to slow it down, mostly thanks to rising wealth and women's education, and to advances in family planning (Chandrashekhar, 2019).

Lastly, the ***carbon intensity of energy*** driver maintained a positive contribution to the change in emissions throughout the four subperiods, even though at a declining fashion. Indeed, as of 2018, India's TPES still constituted in its 71.5% of fossil fuels, with this country's coal consumption increasing by 8.7% in 2018. This seems to point to the fact that India lacks the declining trend for coal that was generally observed for the other countries object of this analysis. Moreover, 28.5 % of India's TPES in 2018 consisted of renewables and nuclear energy, which is the same share observed in the preceding year, and 2.7 percentage points lower than the corresponding figure for 2010 (Olivier and Peters, 2020). This declining trend in the use of non-fossil energy is peculiar of India, and different from what has been observed so far in the other countries object of this study, showing that there is still a lot of room for improvement in this ratio for India, which could result in a slowdown of the emissions' growth for this Country. Considering that India ratified the Paris Agreement, which requires, by 2030, that non-fossil cumulative power generation capacity should be of the 40% (Climate Action Tracker, 2019), further efforts towards a "better" fuel mix should be put in place to ensure the meeting of this target.

2.3.6 The Russian Federation

The Russian Federation is the lowest ranking emitter among the ones considered in this study, with its 2017's 1,537 million tons of fossil CO_2 emissions (IEA, 2019a) making up an approximate 5% of the global ones.[12] This Country experienced a massive drop in its emissions after 1990, following the fall of the Soviet Union, initially paired with an equally as massive drop in its economy (Chirmiciu and Dosi, 2011). Nevertheless, while the economy sharply recovered, reaching 1990 GDP per capita levels in 2006, emissions stabilized at much lower

[12] Number based on Author's computations from IEA data relative to fossil CO_2 emissions in 2017 (IEA, 2019a).

levels than the ones observed at the beginning of the study period, with the Russian Federation's 2017 fossil CO_2 emissions values being about 30% lower than the corresponding 1990 ones.

The LMDI I decomposition of the change in fossil fuel CO_2 emissions for the Russian Federation is proposed in Figure 15.

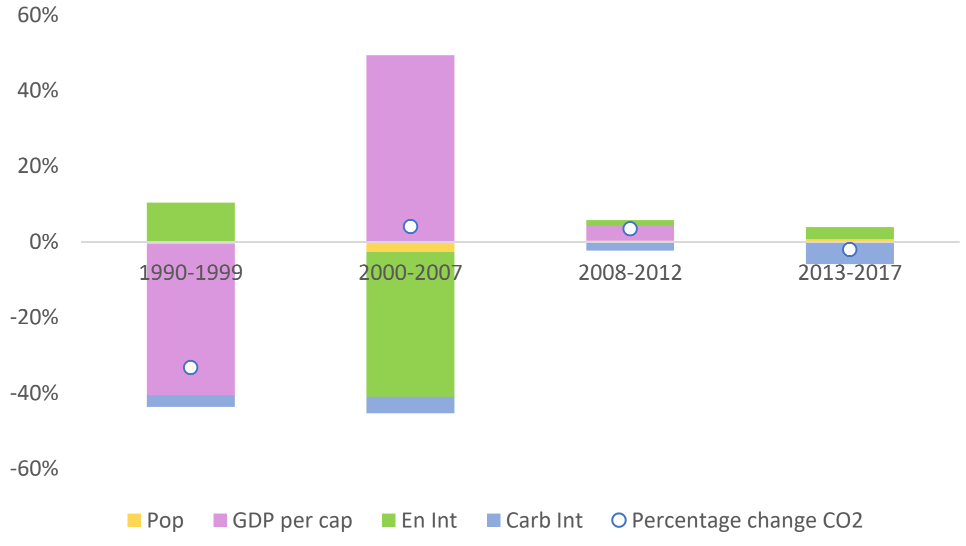

Figure 15 - Russian Federation's fossil CO_2 emissions decomposition. Source: Author's own elaboration based on IEA and UN Stats data (2019).

The sharp decrease experienced in the Russian Federation's emissions following the Soviet Union's fall is made evident by the 33% decline observed in the 1990-1999 subperiod. Afterwards, the two central subperiods, namely 2000-2007 and 2008-2012, show single-digit increases in emissions, followed by a mild decline of about 2% in the last subperiod.

Concerning the driving factors, the ***carbon intensity of energy*** has a consistently negative contribution to the change in emissions. This reduction is mainly because of an observed shift from coal and oil, towards natural gas and, in smaller part, renewables and nuclear power (Chirmiciu and Dosi, 2011; Olivier and Peters, 2020). As a matter of fact, as of 2018, according to Oliver and Peters (2020), 49.8% of Russian TPES comes from natural gas, while oil and coal together account for a 38.6% share, and renewables and nuclear for the 11.6%. The root of this phaenomenon is the lower energy demand for carbon-intensive fuels from both the industry and power sectors, with several coal-based power and heat generation capacities not being used anymore (Chirmiciu and Dosi, 2011).

The ***population*** driver has a negligible influence on the change in emissions across all the subperiods considered, with its contribution sign being negative in the first two subperiods, and positive in the last twos. This is because population changes have been of little entity over the entire period considered (Chirmiciu and Dosi, 2011), with the 2017 population being only about 2.6% lower than in 1990.[13]

The ***GDP per capita*** driver, as could be expected, exerted a negative contribution in the first subperiod, namely 1990-1999, due to the massive economic shock experienced after the fall of the Soviet Union, which was the main cause of the emissions' decrease observed in that same subperiod, given that, in the absence of any GDP per capita change, and with all the other driving factors equal, emissions would have increased 7% instead of declining. Successively, this factor exerted a positive contribution to emissions' variation in the two subsequent subperiods (i.e. 2000-2007 and 2008-2012), following the economic recovery that took place in those same years, to then exert a negative, but negligible, pressure in the last subperiod considered, namely 2013-2017. This last sign change is to be imputed to the international economic sanctions imposed to the Country following the Russian invasion of Ukraine, which began in 2014, and contributed to the financial crisis that hit the Russian Federation in 2014 and 2015, culminating with the Russian ruble being devaluated, and also to the oil price drop of the second half of 2014 (Olivier and Peters, 2020).

Lastly, the ***energy intensity of GDP*** driver changed the sign of its contribution to emissions' variation, which has been positive in all subperiods but the 2000-2007 one. Indeed, the Russian Federation inherited from the Soviet Union a pretty energy-intensive production scheme, related in great part to the large availability of fossil-fuel resources in this Country, and to energy under-pricing (Chirmiciu and Dosi, 2011), which may explain the positive contribution of this driver in the first considered subperiod. However, the major positive influence exerted by the economic recovery to the emissions' variation in the 2000-2007 subperiod, has been almost entirely offset by the improvement in the energy intensity of GDP ratio, suggesting efforts towards a less energy-intensive production and a more efficient use of energy. Indeed, both structural changes in the Russian economy and sectoral efficiency improvements contributed to this decrease. In the last two subperiods, the contribution of this driver returned to be positive, although the trend of this ratio remains generally declining with respect to 2000 levels, as will be pointed out in the next Chapter.

[13] Number based on Author's computations from IEA data (2019a).

2.4. Results summary

To conclude this first-level decomposition analysis, it is worth to briefly review similarities and differences across the considered countries.

First, one fact that really stands out is that, in general, exception made for the case of the Russian Federation, the main driver which induced a positive effect on the emissions' change has been the GDP per capita, whereas the main driver which induced a negative effect has been the energy intensity of GDP.

In addition to that, it is important to note how the developed economies, namely ***Germany***, the ***UK***, the ***US*** and, even if to a lower extent, ***Italy***, have experienced a reduction of CO_2 emissions, while maintaining at the same time a generally good degree of economic growth. On the other hand, the emerging economies of ***China*** and ***India*** experienced a massive economic development, which was accompanied by an as important growth in their emissions, with China, however, reducing its growth rate remarkably in the last subperiod considered. Lastly, the case of the ***Russian Federation*** stands out for itself, as it underwent a recovery process from the Soviet Union fall-induced economic shock, which brought up a massive drop in the emissions produced by this country that, despite the economic recovery, managed to stabilize and not spike back up again.

However, a closer look at the data reveals further insights. In fact, in the cases of Italy and the UK, during the Great Recession's subperiod, the GDP per capita driver turned to a negative contribution sign, while in Germany and the US it significantly reduced its positive contribution. In spite of the fact that, in the recovery subperiod that followed the Great Recession, the contribution of this driver changed its sign, in the case of the first two countries, and increased its positive contribution, in the case of the latter countries, the emissions managed to continue along their declining path, suggesting an absolute decoupling between the GDP per capita driver, and the fossil CO_2 emissions. Moreover, while in China emissions have continued to increase, it appears, especially in the last subperiod considered, that they have been doing so at a much lower rate with respect to the GDP per capita, which seems to point to relative decoupling between the two variables.

For this reason, to gain further insight on the matter and effectively formalize the relationship between economic growth and environmental damage, the use of a decoupling analysis appears to be necessary, in order to also understand how this relationship has changed throughout the analysed period and, more specifically, if the Great Recession, which inevitably led to a decline in emissions in some of the studied countries, had any impact on this relationship.

2.5. The decoupling analysis and Tapio decoupling methodology

As already pointed, out, the decoupling analysis can be seen as a mean to assess the link between two of Kaya's Es, namely environmental quality and economic development.

Concerning the relationship between those two items, several studies considered the Environmental Kuznets Curve (EKC) hypothesis as the starting point. According to this theory, used for the first time in 1992 to describe the relationship between sulphur dioxide concentrations and GDP per capita, the two variables interact following an inverted U-shape (Agbugba et al., 2019). This same relationship has been later extended to the one between GDP per capita and environmental damage, implying that, initially, an increase in the former causes an increase in the latter, but, after a turning point is reached, GDP per capita continues to grow, whereas environmental degradation starts to decline. This relationship is summed up in the graph reported in Figure 16.

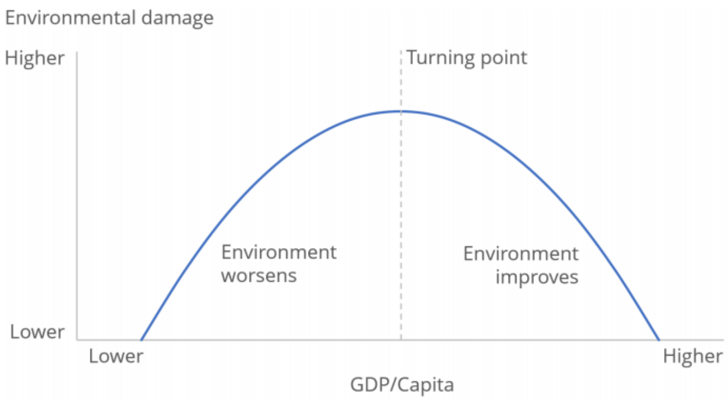

Figure 16 - Environmental Kuznets Curve. Source: Agbugba et al., 2019.

Relying on the EKC hypothesis means that an increase in per capita GDP or, more generally, in the economic development of a country, is expected to lead, eventually, to a structural shift in the economy of said country, from a more rural and industry-based economy, to a more service-based one. Moreover, a more developed economy will also bring about technological advancements, which reduce the amount of GHG emissions produced. Lastly, economic development also brings to environmental concern, from both consumers and governments, which may enact regulations to contain environmental degradation. This theory, for as widely accepted and recognized in the literature, presents however one main shortcoming: it does not consider the export of carbon-emitting activities which is operated by the advanced economies, towards developing countries with lower labour costs (and less stringent environmental regulations), such as China (Agbugba et al., 2019).

Despite this main shortcoming, it is interesting however to assess if indeed a relationship of the sort described by the EKC hypothesis holds in reality. In order to do that, the decoupling analysis seems to respond well to the task. Decoupling can be detected when “the growth rate of an environmental pressure (for example, CO_2 emissions) is less than that of its economic driving force (for example, GDP per head) over a given period” (Agbugba et al., 2019). Decoupling is said to be absolute when the environmental pressure is stable or degrows while the economic driver grows, or relative, when the two variables both grow, but the former does so at a lower rate.

To investigate decoupling relationships among environmental and economic variables, two main techniques have been adopted: the OECD and the Tapio decoupling methods. Among them, Tapio decomposition has been preferred in this study, as it renders more stable results and includes more detailed categories for the decoupling states with respect to the OECD method, that only assesses whether the decoupling is absolute or relative (Lin et al., 2015; Chen et al., 2018). This technique relies on the computation of decoupling elasticities, that are given by (Liu et al., 2015):

$$d = \%\Delta EP/\%\Delta DF$$

With d being the decoupling index, or elasticity; $\%\Delta EP$ being the percentage change in the environmental pressure between the two years considered; and $\%\Delta DF$ being the corresponding quantity for the driving factor considered. After retrieving the value of d, it is possible to fit the relationship between the two variables considered into one of eight possible categories, according to the Table C.1, reported on the APPENDIX C. These categories have been constructed considering a ± 20% variation of the elasticity values around unity as a confidence interval for coupling, in order not to mistakenly interpret as decoupling a fairly small change around unity (Tapio, 2005; Liu et al., 2015).

The results obtained from the Tapio decoupling analysis applied to the seven countries object of this study, relatively to the relationship between the fossil CO_2 emissions and the GDP per capita driver across the four subperiods, and for the entire sample are summed in the following, but numerical results can be reviewed in Table C.2 of APPENDIX C.

First, ***Germany*** exhibited strong decoupling across the four subperiods and also relatively to the entire sample. This basically means that, while the indicator of environmental damage used, namely fossil CO_2 emissions, declined in the whole sample, the indicator of economic development used, namely GDP per capita, increased for the same time reference. This means that Germany effectively managed to obtain an absolute decoupling between its emissions and its economic growth, by more than compensating the environmental pressure exerted by economic development with improvements in other driving factors, such as, for the most part, the energy intensity of GDP and, to a smaller extent, the carbon intensity of energy, fostered by technological and fuel mix improvements.

A similar development was observed in the ***US***, which, first subperiod aside, displayed strong decoupling between the two variables considered. The weak decoupling observed in the first subperiod, which means that both emissions and the GDP per capita increased, but with the former increasing at a slower rate than the latter, is basically conceptually the same as a relative decoupling relationship. This is because, indeed, the US' downward trend in emissions saw its beginnings after the year 2000, while emissions were still on an increasing trend in the first subperiod analysed, namely the one from 1990 to 1999.

In both these first two cases, the outburst of the Great Recession did not seem to have any visible impact on the observed absolute decoupling relationship, except for a shrinking in the value of the decoupling elasticities of the last subperiod, which seems to point to a lower order of magnitude, although of opposite sign, of the percentage variation in emissions with respect to the one of the economic driver. This is probably related to the fact that, while the economic development slowed down in the crisis subperiod, the declining path of emissions was, in a way, even stimulated by the economic downturn, most likely because of a reduction in the output. This implied that, while the economic recovery brought to a greater growth in the GDP per capita, the decline in emissions did not experience a change in the same order of magnitude.

Two countries that, on the other hand, experienced a similar development in the decoupling relationship between the two studied variables which has been affected by the advent of the Great Recession are ***Italy*** and the ***UK***. Indeed, the two countries displayed, in the subperiod preceding the crisis (i.e. 2000-2007) an "expansive coupling" (i.e. both emissions and GDP per capita increased, at approximately the same rate) and a weak decoupling relationship, respectively, followed by "recessive decoupling" in the 2008-2012 subperiod, to then turn to strong decoupling in the last subperiod (i.e. 2013-2017). Recessive decoupling is observed whenever both the emissions and the GDP per capita driver decrease, but with the former doing so at a faster rate. This implies that, while the Great Recession negatively impacted the economies of these two Countries, with adverse consequences on both the emissions produced and GDP per capita, the economic recovery which occurred in the last subperiod did not come at the expense of the environment, meaning that an absolute decoupling between the two variables prevented the economic recovery to be accompanied by spikes in emissions. Lastly, when considering the entire time window of this study, both Countries displayed a strong decoupling relationship, whereas in the first subperiod Italy experienced a weak decoupling, owed to a positive growth in emissions in those years, as opposed to the strong decoupling experienced by the UK, linked to its declining emissions observed in those years.

The last three countries' GDP per capita was virtually unaffected by the Great Recession, but changes were still observed in the decoupling relationship between the two considered variables.

The ***Russian Federation*** alternated, throughout the four subperiods, coupling and decoupling relationships. The first subperiod, which was the one immediately after the fall of the Soviet Union, showed a recessive coupling relationship, which implied that the massive drop experienced in Russian emissions was extensively owed to the massive economic shock which hit the Country in those years, since the decoupling elasticity had a value close to one. The second subperiod, characterized by the economic recovery, showed evidence of weak decoupling, meaning that, although the GDP per capita went back up, emissions did increase, but at a much slower rate. The Great Recession subperiod was characterized by a return to a coupling relationship, with both the emissions and GDP per capita increasing, at roughly the same rate. Nevertheless, the most hardly felt crisis subperiod for this Country was the last one, characterized by falling GDP per capita and emissions, but with the latter declining at a faster rate. This kind of relationship is labelled as recessive decoupling and is conceptually similar to that of relative decoupling. Nevertheless, it appears that the Russian Federation still has not managed to achieve the absolute decoupling which has been observed for the developed economies, even if, when considering the full time period, the relationship between the environmental pressure and the economic development variables is one of strong decoupling, given that, since the Soviet Union fall, this Country has managed to reduce its emissions with respect to base year levels, and, at the same time, undergo sensible economic recovery.

Lastly, both China and India experienced, across the four subperiods, a growth which interested both their economies and emissions, but the way the two variables representing them are intertwined is substantially different for the two Countries. On the one hand, ***China*** experienced weak decoupling in the first and last subperiods, and also when considering the full time window as a whole. However, the central subperiods display a less encouraging picture, with expansive coupling in 2000-2007 and 2008-2012. This means that, in the subperiod characterized by China's access to the WTO and by its most relevant GDP per capita growth (i.e. 2000-2007), both emissions and GDP per capita increased, at roughly the same rate. This is probably because, as previously stated, the economic growth of this Country was mainly driven by pollution and carbon-intensive production. The following subperiod, the one of the Great Recession, was as well one of experienced expansive coupling. The last subperiod, as previously mentioned, ends the decoupling analysis on a better note, as the observed state for this subperiod has shifted to one of weak decoupling, meaning that China's improvements in its energy intensity and carbon intensity ratios assured that, even if emissions still increased, they did at a much slower pace than the Chinese economy, leading to a progressively decoupled relationship between the two analysed items.

This same shift to weak decoupling for the last subperiod considered has been observed in ***India*** and was owed, in its entirety, to a bettering of energy intensity. Nevertheless, the three previous subperiods, and the entire time window considered, display a relationship between the two variables of the opposite direction. Indeed, the first and the third subperiods, other than the full period, exhibit expansive negative decoupling, most likely owed to the carbon-intensive fuel mix utilized in this Country. The second subperiod, namely 2000-2007, showed expansive coupling, owed to the temporary alignment in the growth rates of emissions and GDP per capita.

Of course, this whole reasoning holds only as long as it sticks to *production-based*, or territorial-based, emissions (i.e. emissions that occur within the country's borders – Agbugba, 2019), without considering emissions embodied in the net exports, that make up the so-called *consumption-based* emissions (Cohen et al., 2018). Indeed, a study on decoupling elasticities of the main emitting countries conducted by Cohen et al. (2018) proved that, while the developed economies may have changed their production patterns, they did not change their consumption patterns accordingly, and kept consuming emissions at a similar fashion, by importing it, or by moving their dirtiest production to developing economies such as China and India. This fact materializes in higher consumption-based than production-based elasticities, on average, in developed economies, and in the twos being essentially equal in developing economies. This seems to weaken, but does not annihilate, the evidence for the EKC curve to hold in reality, given that even consumption-based decoupling elasticities turned out to be significantly smaller for developed economies than for the developing ones.

CHAPTER 3: DECOMPOSITION OF ENERGY INTENSITY OF GDP AND CARBON INTENSITY OF ENERGY

3.1. Energy intensity of GDP

3.1.1 An application of the Fisher Ideal index method to industrial energy intensity: data and framework

Energy intensity can be defined, as previously mentioned, as the energy use per unit of economic output for a given country (Metcalf, 2008; Atalla and Bean, 2017). Especially after the first oil crisis of the 1970s, this concept has been object of increasing interest, and investigations for possible improvements in this ratio have been at the heart of several studies on the subject.

In this sense, two main drivers of energy intensity have been widely recognized: the ***structural effect***, and the ***sectoral[14] effect***.

The former includes any structural adjustment towards less energy-intensive sectors, for instance going from an economy strongly skewed towards polluting industries to a more service-based one. The latter includes any energy intensity improvements obtained within each sector, which may have occurred thanks to technological advancements, behavioural or product mix changes, or other variables (Metcalf, 2008; Voigt et al., 2014; Atalla and Bean, 2017; Haas and Kempa, 2018).

In this sense, the formula for the energy intensity can be rewritten as (Metcalf, 2008):

$$e_t = \frac{E_t}{Y_t} = \sum_i \left(\frac{E_{it}}{Y_{it}}\right)\left(\frac{Y_{it}}{Y_t}\right) = \sum e_{it} s_{it}$$

Where E_t is the aggregate energy consumption in year *t*, E_{it} is the energy consumption of sector *i* for year *t*, Y_t is a measure of economic output in year *t*, Y_{it} is a measure of economic activity in sector *i* for year *t*. This implies that e_{it} is the energy intensity of sector *i*, at time *t*, while s_{it} is the relative contribution to the overall economic output of sector *i*, at time *t*.

Given this formulation, the entire Section 3.1 will be devoted to the decomposition analysis of the industrial energy intensity (i.e. excluding the energy consumption of households) into the

[14] This effect is also referred to in the literature as the efficiency effect (Metcalf, 2008; Haas and Kempa, 2018) or the technology effect (Voigt et al., 2014).

two aforementioned effects, referring to the same countries which have been used in the previous Chapter. In order to pursue this decomposition, the Fisher Ideal index technique has been used.[15] This will allow to gain further insight onto the main causes which led to the observed changes in this driving factor, and understanding on the interplay between these two effects in each of the studied countries.

For this scope, data on sectoral energy use have been collected from the European Commission Joint Research Centre (EC JRC) World Input Output Database (WIOD) environmental accounts (2019 release, Corsatea et al.). This dataset, used to perform similar analyses to the one pursued in this work (see e.g. Voigt et al., 2014; Andreoni and Galmarini, 2016; Atalla and Bean, 2017) allocates energy use according to the residence principle (i.e. energy use is allocated to the country of residence of the user, and not to the country in which it takes place). This should allow to overcome, at least in part, some of the issues referred to at the end of the previous Chapter, and to obtain a more true-to-reality picture of this ratio. The dataset spans for the time window between 2000 and 2016 and covers more than 40 countries. Energy consumption data are expressed in Terajoules (TJ).[16] For this study, in particular, the "Emission-relevant Energy Accounts" have been used because, as stated by Atalla and Bean (2017), they exclude energy used as a feedstock, and well match the Total Primary Energy Supply data reported in IEA's Energy Balances.

The indicator of economic activity employed is the value added by sector, computed at constant 2015 prices and expressed, through exchange rates, in USD, provided by the same UN Stats database (2019) which has been used in the previous Chapter. This measure of economic activity has already been used in decomposition studies, such as those from Xu and Ang (2013), and Chirmiciu and Dosi (2011).

Accordingly with the time coverage of the WIOD, the time window used in this Section is 2000-2016. Indeed, relying on the previous releases of this Dataset to enlarge the time window so it would match the one of the previous Chapter would have inevitably led to structural break and data inconsistency, given that previous releases did not rely on the residence principle, which is a novelty introduced with the latest release.

Lastly, while the WIOD dataset subdivides industrial energy use into 56 different sectors, the UN Stats dataset only subdivides the total value added into 6 different sectors. This required to

[15] Further detail on the formulae used for this decomposition can be found in APPENDIX D.1.

[16] 1 Terajoule = 10^{12} Joules.

operate a sectoral grouping, which has been reported in full in Table D.1 of APPENDIX D. The sectors obtained from this clustering are:

1. ***Agriculture, hunting, forestry, fishing***;
2. ***Mining, Manufacturing, Electricity, Utilities***, including equipment, food, and metals manufacturing, water collection, treatment and supply, and waste collection;
3. ***Construction***;
4. ***Wholesale, retail trade, restaurants and hotels***;
5. ***Transport, storage and communication***;
6. ***Other Activities***, which incorporates all service-based activities, such as consultancy activities, financial services and insurance, and other professional, scientific and technical activities.

3.1.2 Germany, United Kingdom and Italy

Germany

Exception made for a slight increase experienced in the first years of data considered and for isolated increases experienced in 2007 and 2010, Germany's industrial energy intensity has been on a declining trend since 2003.

By applying the Fisher Ideal index decomposition, it turns out that these observed efficiency improvements were to be imputed in their entirety to the sectoral effect. Indeed, the structural effect even brought to an increase of this ratio. Figure 17, reporting the decomposition analysis results, represents the interplay between these two effects and the energy intensity ratio, showing their development between 2000 and 2016, and using 2000 as the base-year reference for any experienced change.

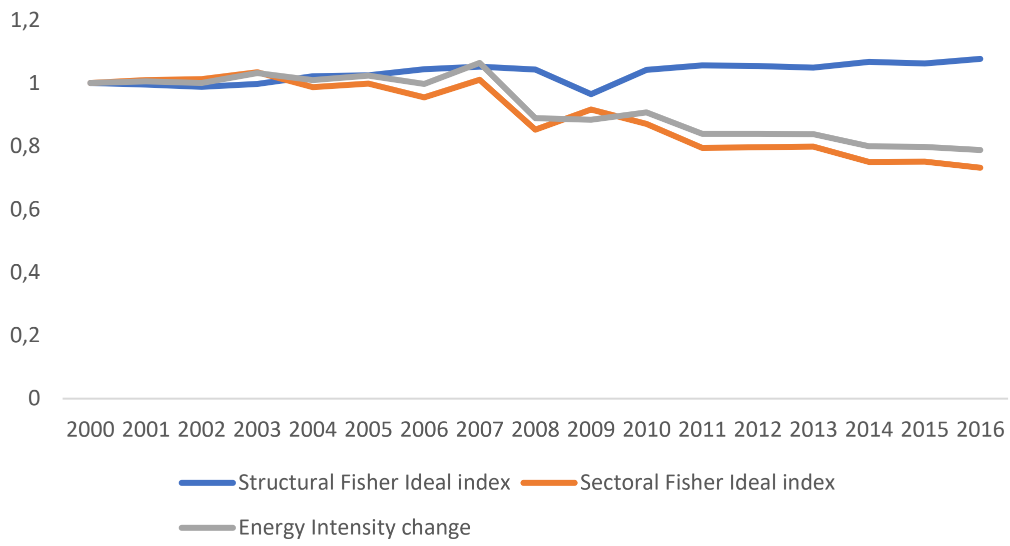

Figure 17 - Germany's industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

Figure 17 clearly shows the afore mentioned declining trend in the industrial energy intensity, with exceptional spikes observed in the years preceding the Great Recession, which were driven entirely by a worsening of sectoral energy intensities, suggesting that, across sectors, during that period, either an higher energy use, or a lower output created, led to an energy intensity increase. In general, the energy intensity curve seems to mimic the evolution of the one for the sectoral driver, even if at a slightly higher level, which is owed to the presence of the structural driver, that, with respect to the base year level, shows an increasing trend, reaching, in 2016, the 108% of its 2000 level. This outcome is backed up by the works of Xu and Ang (2013), Atalla and Bean (2017), who found results consistent with these findings. During the years of the Great Recession, however, a drop in the structural index has been compensated by a spike in the sectoral index, leading the energy intensity line to a flatten between 2008 and 2010.

In order to get to the root of the observed development of the two drivers, two graphs are presented in Figure 18.

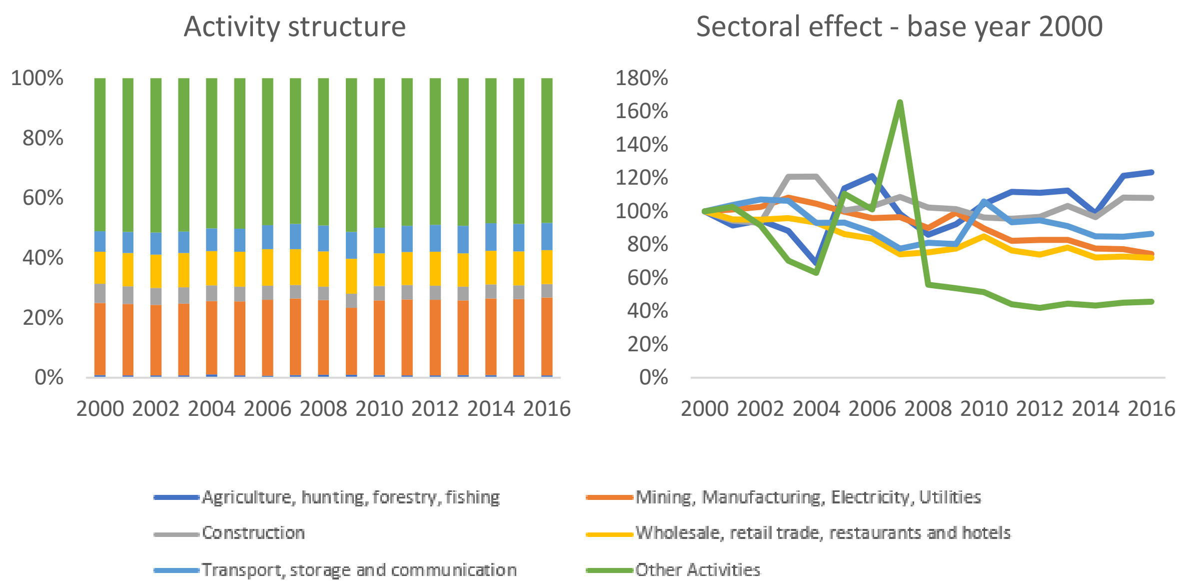

Figure 18 - Structural and sectoral effects for Germany. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

The graph on the left shows the evolution of the industrial structure of Germany, for all the considered years of data. It is evident how the structure of the German economy has not changed much. Indeed, the sector which accounted for the most value added in 2000, namely "Other Activities", still had the highest percentage contribution in 2016, with a mere 2,8[17] decrease in its relative importance. This points to a service-based economy, with especially little relevance of the primary sector, materialized in its 2016's 0,73% share on the overall value added, accompanied, however, by a great significance of the manufacturing sector. Indeed, what probably led to the increase observed in the structural index was the increased share experienced in more energy-intensive sectors, such as "Mining, Manufacturing, Electricity, Utilities", whose share went from 24,1% in 2000, which is already quite relevant, to 26% in 2016, and "Transport, Storage and Communication", whose share went from 10,7% in 2000 to 11,3% in 2016. These two shifts, coupled with a declining relevance of the "Other Activities" sector, has caused the positive contribution sign of the structural effect to the change in energy intensity. For what concerns the dip observed in 2009 relative to this effect, it is owed, for the most part, to a 3% annual drop in the share of the "Mining, Manufacturing, Electricity, Utilities" sector's value added experienced in that year, which led to a temporary decline of the entire structural effect. The observed structural shift towards more energy-intensive sectors, which, however, in the analysed time window, experienced efficiency improvements, has been commented also by Voigt et al. (2014).

[17] All numbers and percentages cited in Section 3.1 are based on the Author's own elaboration of WIOD and UN Stats data (2019).

For what concerns the graph on the right, it can be seen how, with respect to their 2000 levels, all sectors but “Agriculture, Forestry, Fishing” and “Construction” experienced reductions in their energy intensities. This is the reason behind the observed declining trend in the sectoral effect contribution. The only spike in this contribution, experienced during the years of the Great Recession, was owed to a great increase in the “Other Activities” sector’s energy intensity, that, in 2007 reached the 166% of its 2000 level.

United Kingdom

The UK’s industrial energy intensity has been, exception made for a small increase experienced in 2009, declining for the entire time window considered, reaching, in 2016, the 61,4% of its 2000 level. This has been driven, according to Voigt et al. (2014) both by a reduction in energy use, and a contemporaneous increase in gross output, which seems to point to an absolute decoupling between these two quantities.

From the results of the decomposition analysis, it turns out that the UK’s energy intensity decline is to be imputed, after 2002, in equal parts to the structural effect, with the structural Fisher Ideal index for 2016 being the 81% of its 2000 level, and to the sectoral effect, with the sectoral Fisher Ideal index for 2016 being the 76% of its 2000 level (Figure 19). The importance of both effects in the energy intensity reduction has been observed also by Atalla and Bean (2017). For the first years of the considered period the structural effect had a primary role in contributing to the energy intensity’s decline, with this driver even being the only negative contributor in 2001, but the situation reversed after 2007. Indeed, unlike Germany, the UK underwent significant structural changes, as will be explained in further detail. Lastly, the small 2009 increase in industrial energy intensity is to be ascribed to a temporary worsening of sectoral energy intensities, made evident from Figure 19.

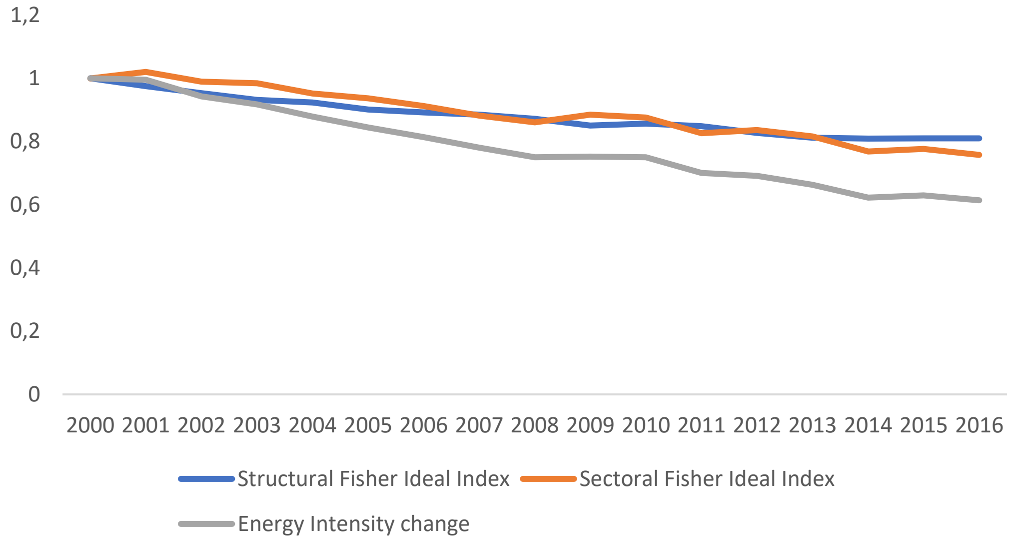

Figure 19 - UK's industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

As before, Figure 20 reports two graphs helpful for disentangling the two studied effects.

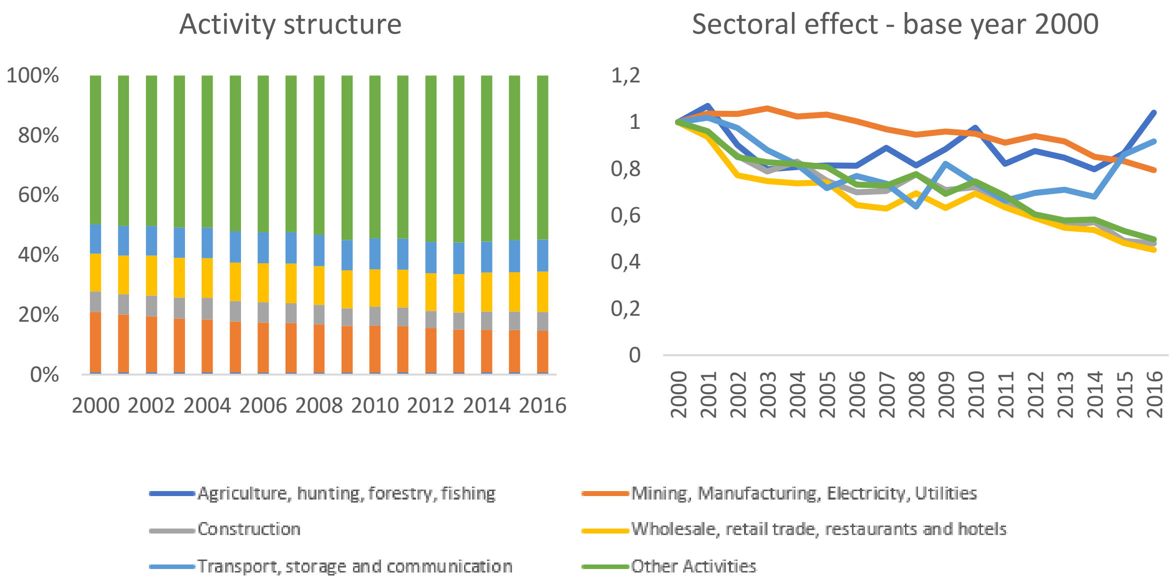

Figure 20 - Structural and sectoral effects for the UK. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

The graph on the left shows a continuous development in the industrial activities' structure of this Country. Indeed, the share of the "Other Activities" sector is increasing throughout the entire period, gaining about 5 percentage points across the full period, counterbalanced by a decline in the share of the "Mining, Manufacturing, Electricity, Utilities" sector, losing about 6 percentage points across the full period. This points to a shift from a manufacturing towards a service-based economy, with particular relevance of the finance, professional services, and information and communication technology sectors, as previously observed by Agbugba et al.

(2019), who studied the structural change in the UK between 1948 and 2016. This kind of structural change is one that contributes to emissions' and energy use's reductions.

The graph on the right represents a much more volatile situation with respect to the one of Germany. In this case, exception made for the "Agriculture, Forestry, Fishing" sector, all sectoral energy intensities have declined between 2000 and 2016. The most remarkable efficiency improvements have been observed in the "Other Activities", "Wholesale, retail trade, restaurants and hotels" and "Construction" sectors, which reached, in 2016, an energy intensity equal to half of the corresponding 2000 levels. Given, however, that these were not, even in 2000, particularly energy-intensive sectors, in absolute values these halving in their energy intensities is not as remarkable. Nevertheless, even the two most energy-intensive sectors, namely "Mining, Manufacturing, Electricity, Utilities" and, to a lower extent, "Transport, Storage and Communication", reduced their energy intensities, accounting respectively, for 21% and 9% decreases over the whole period. Lastly, the 2009 spike in the sectoral effect is probably linked to the annual 29% increase experienced in that year in the "Transport, Storage and Communication" sector's energy intensity.

Italy

During the studied period, Italy's industrial energy intensity first increased, until 2004, to then develop a declining path. Overall, there has been, over the full sixteen years of data, an aggregate reduction in the energy intensity of 1,3%, the smallest observed up to this point. This almost negligible change in the observed energy intensity may be, as Andreoni and Galmarini (2016) pointed out, because of the fact that the per capita energy use in Italy stabilized only in the late 2000s. It should be noted however, that Italy already had a lower energy intensity than its European counterparts at the beginning of the study period. As highlighted in Figure 21, the experienced reduction was owed, in its entirety, to changes in the structure of the Italian economy, whereas, in general, there has been a worsening in the sectoral energy intensities. Indeed, the Structural Fisher Ideal index of 2016 is the 95% of its 2000 value, whereas the Sectoral Fisher Ideal index of 2016 is the 104% of its 2000 value. This same decomposition outcome has been observed by Voigt et al. (2014), who pointed out the fact that structural adjustments towards less energy-intensive sectors were hindered in their contribution to energy intensity reduction by a constant increase in the sectoral effect.

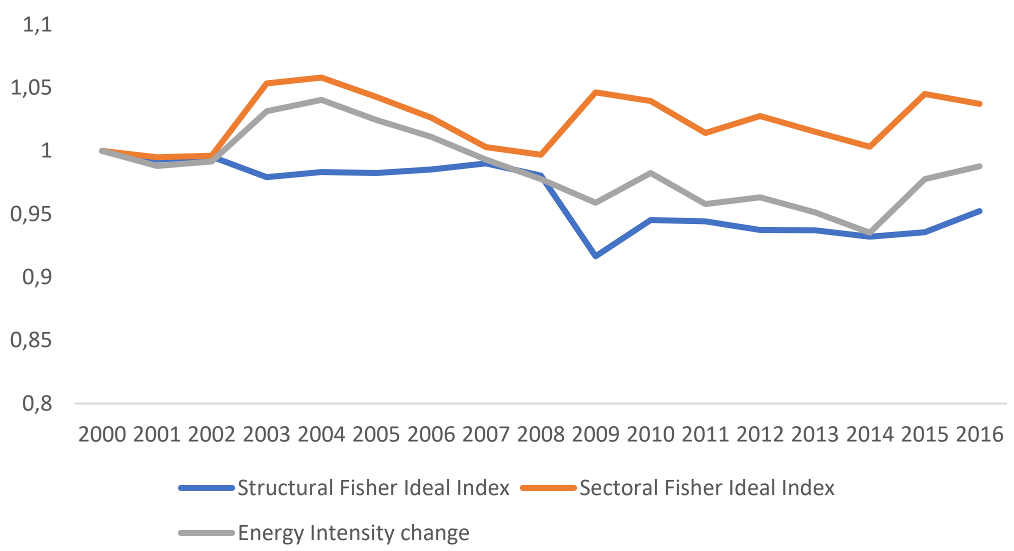

Figure 21 - Italy's industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

In order to obtain further insight regarding the roles of the two effects, Figure 22 reports two graphs shedding a light on the drivers behind each of those factors.

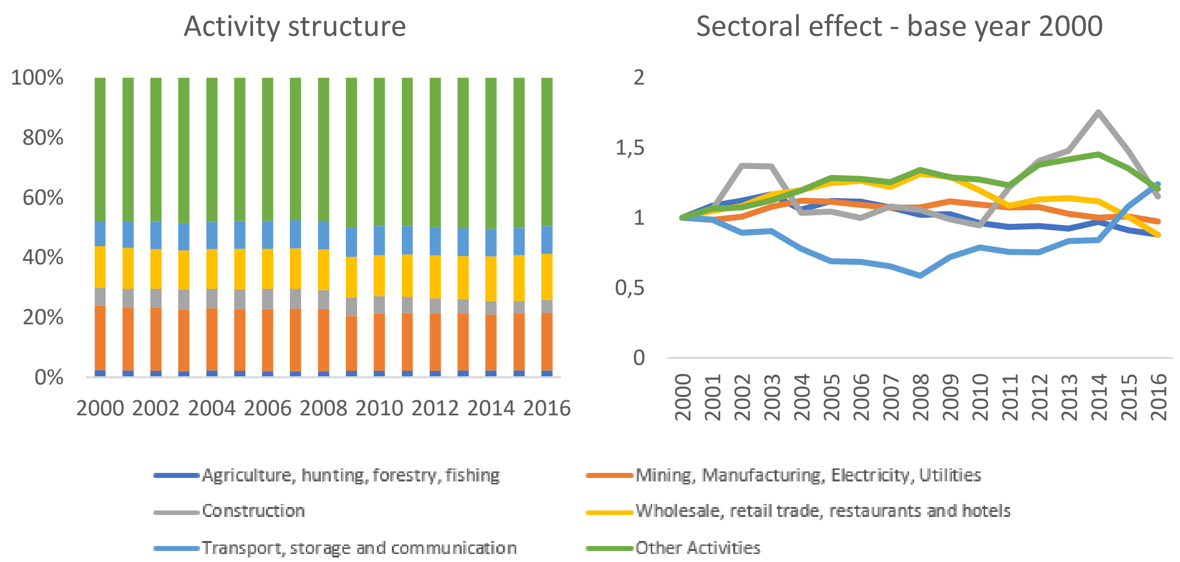

Figure 22 - Structural and sectoral effects for Italy. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

The graph on the left marks the experienced structural change in the Italian economy. As a matter of fact, during the sixteen years of data analysed, less energy-intensive sectors, namely "Wholesale, retail trade, restaurants and hotels" and "Other Activities", increased their percentage share on the total value added of 1,6 each, with the latter reaching a share of 49,5% in 2016. On the other hand, the share of more energy-intensive sectors has decreased, as can be noted by the 2,4 sixteen-year reduction in the percentage share of the "Mining, Manufacturing, Electricity, Utilities" sector. The combination of these two experienced changes in sectoral relative importance led to a shift towards less energy-intensive industrial sectors, which in turn led to the declining trend observed for the structural effect throughout the entire time window.

On the other hand, the graph on the right shows a much less encouraging picture. In fact, the majority of the sectoral energy intensities have either increased or approximately remained the same with respect to their 2000 levels, with the sole exceptions of "Agriculture, Forestry, Fishing" and "Wholesale, retail trade, restaurants and hotels", which experienced mild decreases in the order of ten percentage points throughout the full period. Of remarkable importance were the energy intensity spikes observed in 2014 for the "Construction" and "Other Activities" sectors. This increasing trend in sectoral energy intensities has been the cause of the volatile, but overall growing, pattern of the sectoral effect.

However, since the two effects counterbalanced each other, the overall energy intensity did decrease in 2016, with respect to its 2000 levels, albeit to a smaller extent with respect to the other European economies considered.

3.1.3 United States

The US industrial energy intensity has been declining over the considered period, reaching, in 2016, the 73,4% of its 2000 level. This decline, as can easily be seen from Figure 23, was owed entirely to the improvement of sectoral energy intensities, whereas the structural effect showed very little volatility around its 2000 value. This result may appear at odds with those of the similar analyses made by Voigt et al. (2014) and Atalla and Bean (2017), who claimed the exact opposite to be true, but nevertheless does not contradict them, since their analyses stop, respectively, at years 2007 and 2009, and therefore do not account for the successive slight increase experienced in the structural index, which, indeed, as per their claims, did have a significant role in the reduction of the industrial energy intensity until 2005.

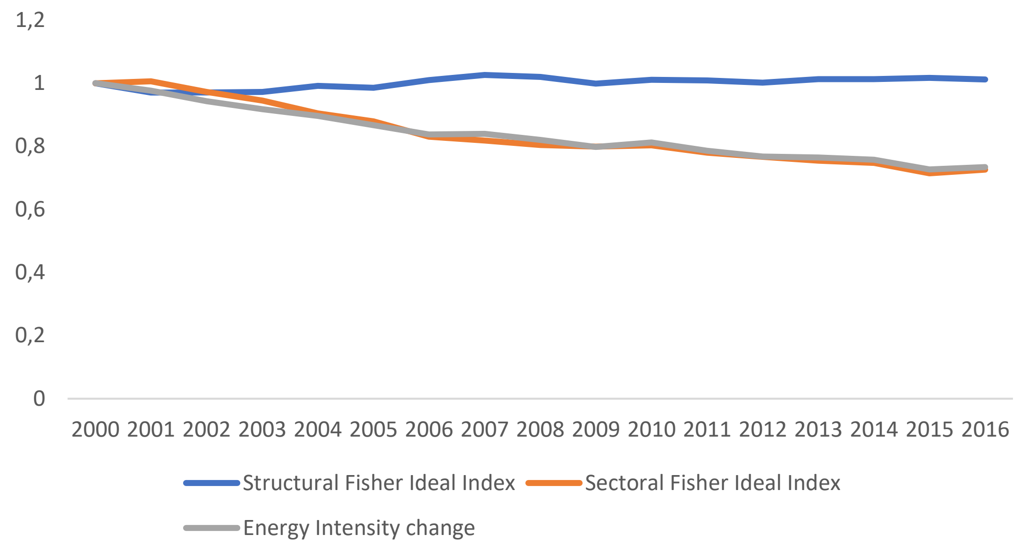

Figure 23 - The US industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

Figure 24 addresses the causes behind the observed changes in the two driving effects.

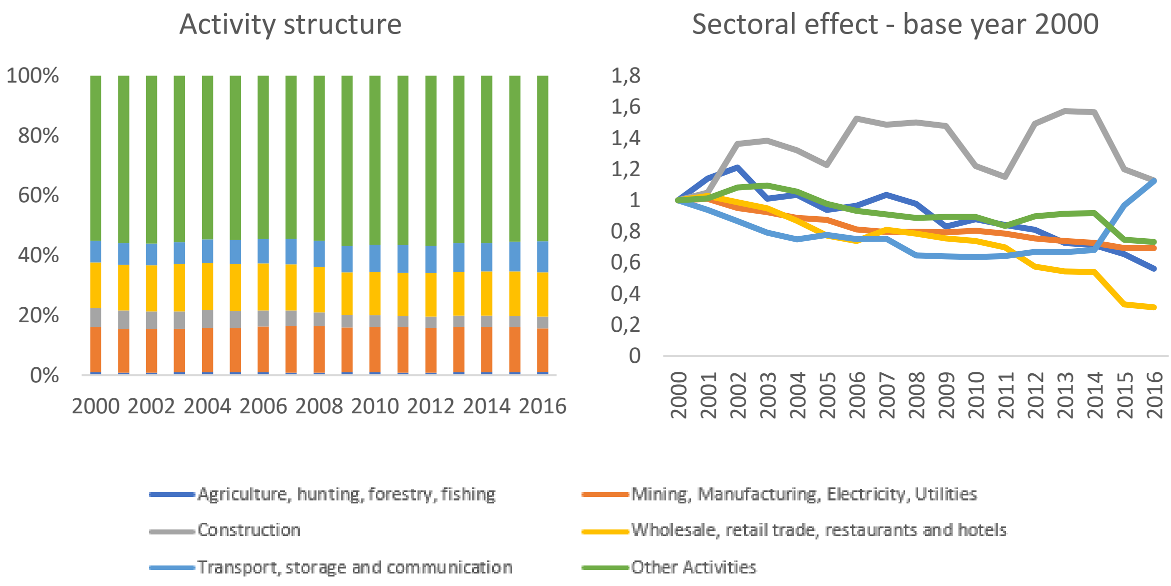

Figure 24 - Structural and sectoral effects for the US. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

The left graph shows, as predicted, an almost unchanged industrial structure of the US economy. Indeed, the sixteen-year absolute change in the sectoral share on the total value added is in the order of one percentage point for all sectors but the “Construction” and the “Transport, Storage and Communication” ones, which showed, respectively, a 2 decrease and a 3 increase in their percentage shares, basically offsetting one another.

On the right-hand graph, nevertheless, a much more dynamic situation emerges. Indeed, aside for the "Construction" and the "Transport, Storage and Communication" energy intensities, which showed mild increases in their 2016 energy intensities, relative to their base-year levels, all the other sectors improved their energy efficiencies. The most remarkable improvement was observed for the "Wholesale, retail trade, restaurants and hotels" sector, which reached, in 2016, the 31% of its 2000 level. This improvement led this sector to become the most energy efficient among the considered ones for the US.

Despite their improvements, it should be noted that the US still rank as the country with the fourth highest energy intensity among the ones considered, and the first among the developed economies.

3.1.4 China

Except for the spike experienced in the years right after China's accession to the WTO and before the Great Recession's advent (i.e. between 2003 and 2007), China's industrial energy intensity has been on a declining path for the entire time window considered. This development, as underlined by Figure 25, is to be entirely imputed to sectoral efficiency improvements, with the curve for the aggregate energy intensity mimicking that of the sectoral effect, even if at a slightly higher value. Indeed, the structural effect, if anything, exerted a slight positive pressure on the energy intensity change, signalling that the Chinese economy had been shifting towards more energy-intensive sectors, or remained more or less the same, despite the achievement of technological progresses that may have improved the within-sector efficiencies. The role of the two effects found is consistent with the results of the analyses performed by Voigt et al. (2014), Atalla and Bean (2017), and of those of Song and Zheng (2012), who found the 90% of the energy intensity change in China between 1995 and 2009 to be imputable to the sectoral effect.

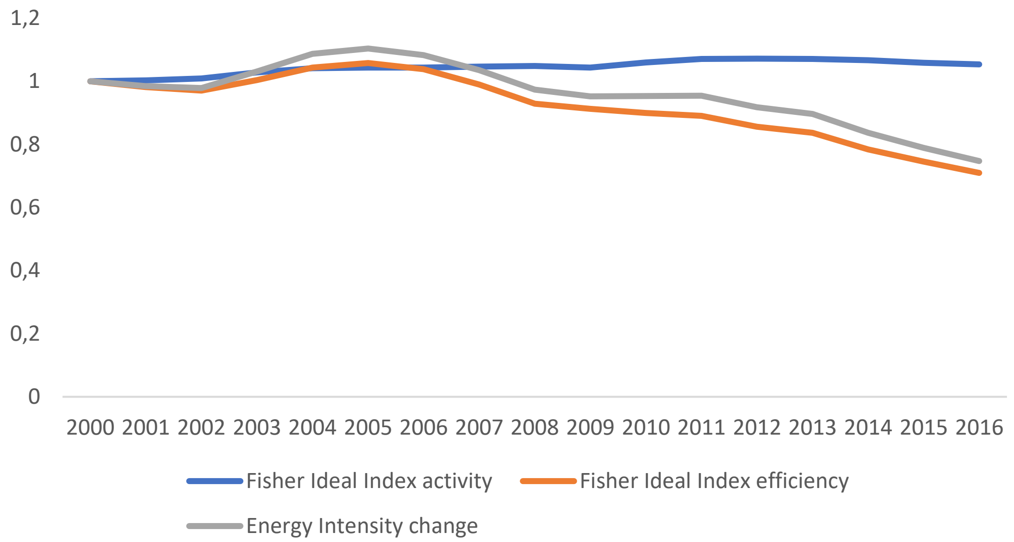

Figure 25 - China's industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

As made evident from the left graph of Figure 26, the Chinese economy rested, in 2016, for the 34,3% of its total value added, on the "Mining, Manufacturing, Electricity, Utilities" sector and, for the 34,6%, on the "Other Activities" sector. Indeed, both those sectors have increased their relative importance in the studied years. What however strikes as the most important structural change has been the sixteen-year 10,5 decrease in the percentage share of the "Agriculture, Forestry, Fishing" sector, whose effects were not as relevant, given its small energy intensity figures.

On the other hand, all sectors improved their energy efficiency, with the most notable progresses observed for the "Wholesale, retail trade, restaurants and hotels" and "Construction" sectors, reaching, in 2016, approximately the 51% of their 2000 levels. What however had a much more relevant impact on the overall energy intensity was the reduction in the most energy-intensive sector's, namely "Mining, Manufacturing, Electricity, Utilities" energy intensity, which decreased, in sixteen years, by 30%. This corresponded, in absolute terms, to a 11,1 Megajoules (MJ)[18]/$ decline, which is higher than the 2016 aggregate industrial energy intensity for China (i.e. 10,2 MJ/$). Lastly, the spike observed in the energy intensity between 2003 and 2007, as made evident from the graph, may have been caused by the increase in the energy intensity of this last sector which occurred in these years.

[18] 1 Megajoule = 1,000,000 Joules.

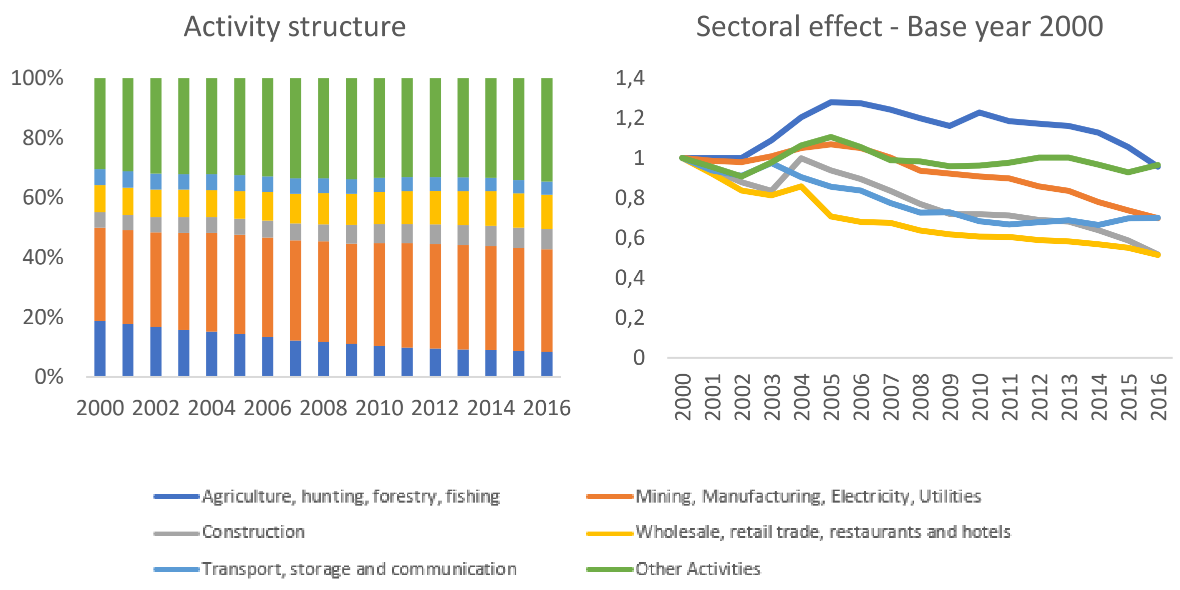

Figure 26 - Structural and sectoral effects for China. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

3.1.5 India

India presents a situation broadly similar to China (Figure 27), with an overall declining trend in its industrial energy intensity, mild positive changes observed for the structural effect, and a persistently declining sectoral effect. This, however, occurred at much higher energy intensity values, with India's 2016 levels being slightly higher than China's 2000 levels. Indeed, India, despite its improvements, reached a much lower reduction in its energy intensity than the other energy-intensive countries considered in this study (i.e. China, Russian Federation, US), although it should be considered that, for instance, China's energy use is much higher than that of India.

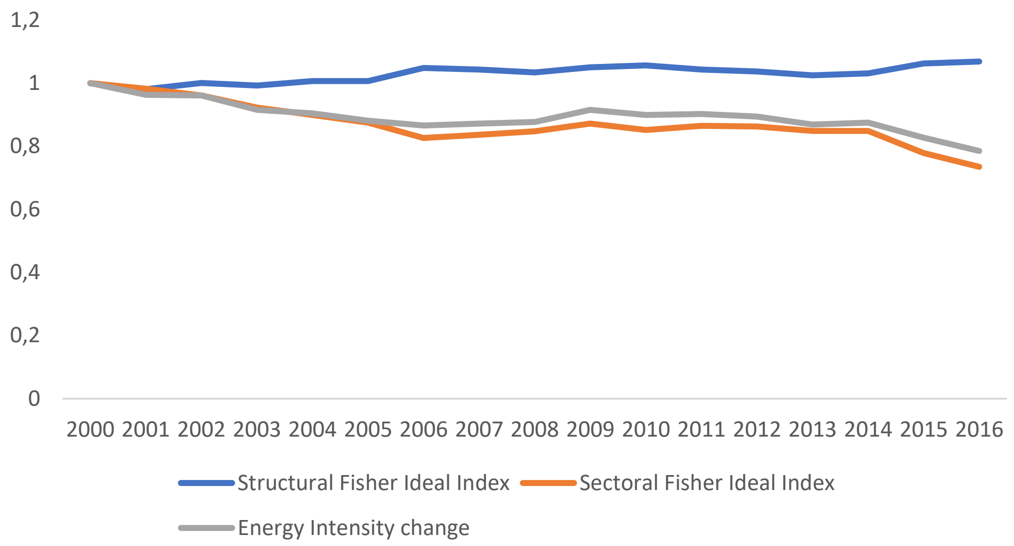

Figure 27 - India's industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

The graph on the left of Figure 28 highlights two evident changes in the structure of the Indian economy, which may have caused the increase observed in the structural effect driver. These are a 13 decrease in the percentage share on total value added of the "Agriculture, Forestry, Fishing" sector, one of the least energy-intensive ones, experienced in the full time window, accompanied, for the same time reference, by a 6,5 increase in the percentage share of the "Transport, Storage and Communication" sector, which is much more energy-intensive, despite the observed efficiency improvements.

Indeed, as can be noted from the right graph of Figure 28, all sectors gained in terms of energy efficiency but the "Other Activities" one, whose energy intensity remained in 2016 at approximately the same level as in 2000, which was already very low. The "Transport, Storage and Communication" is the one which experienced the most relevant improvement, with its 2016 energy intensity level being about 31% of its 2000 level.

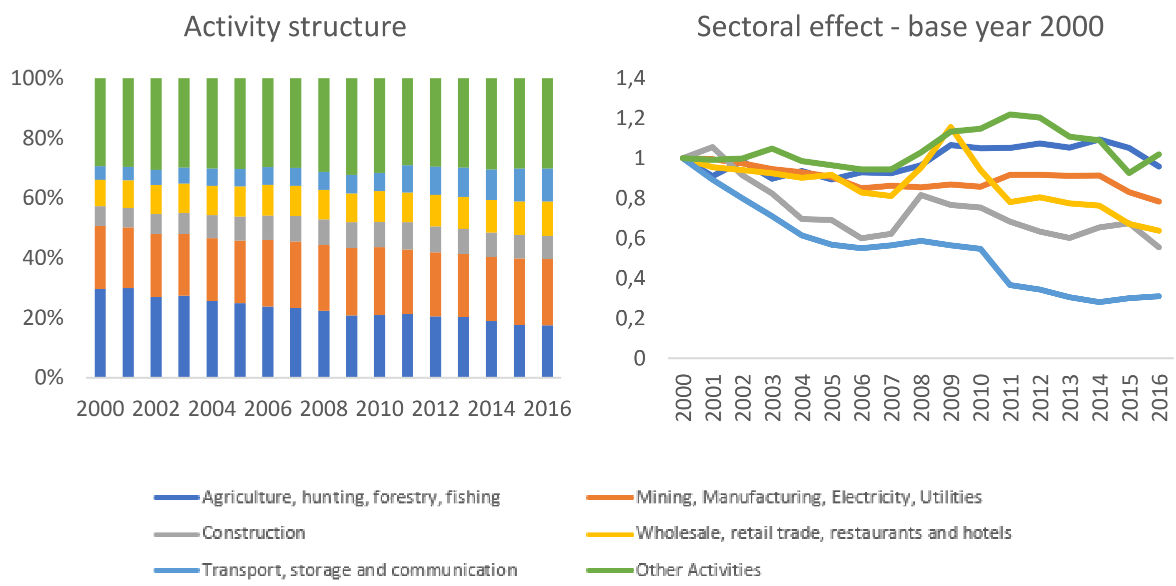

Figure 28 - Structural and sectoral effects for India. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

3.1.6 Russian Federation

The industrial energy intensity of the Russian Federation has been declining for the entire time window considered, due to the effect of both variables analysed. In fact, both factors exerted a negative contribution to the overall energy intensity change, with the structural effect only experiencing a mild increase in the first five years of data analysed (Figure 29).

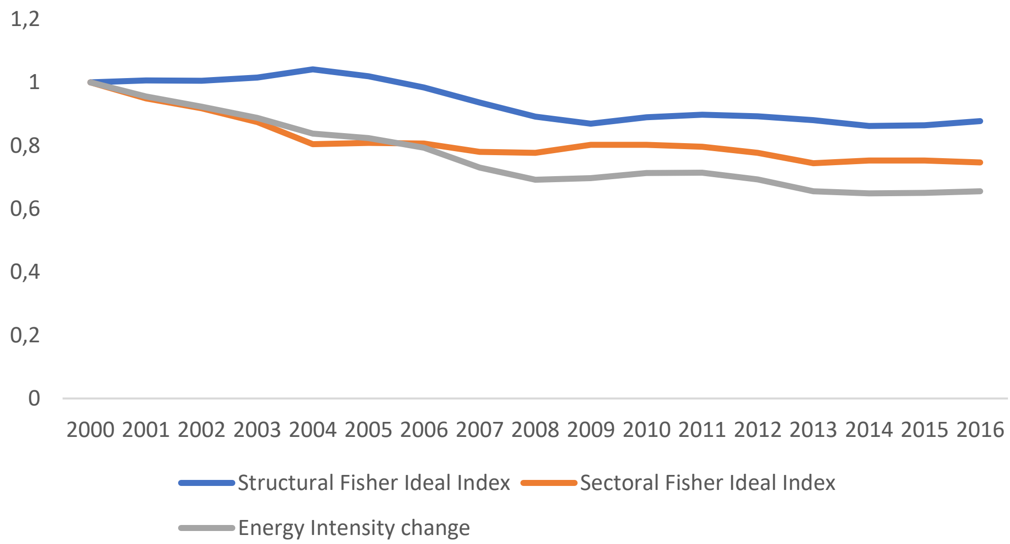

Figure 29 - The Russian Federation's industrial energy intensity change Fisher decomposition, with respect to 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

After an increase in the share on total value added of the “Mining, Manufacturing, Electricity, Utilities” sector, owed to a comeback of heavy industries in the early 2000s (Chirmiciu and Dosi, 2011), which probably is what caused the positive contribution of the structural effect observed in the first five years of data analysed, this same share decreased for the remainder of the period, ranging from 31,3% in 2000 to 26,6% in 2016. This decline was compensated for by a sixteen-year 4,3 increase in the percentage share of the “Wholesale, retail trade, restaurants and hotels” sector, which is characterized by much lower energy intensity, which explains the declining trend in the structural effect after 2005 (Left graph, Figure 30).

On the other hand, all the within-sector energy intensities improved throughout the study period (Right graph, Figure 30). In particular, the “Mining, Manufacturing, Electricity, Utilities” sector’s intensity in 2016 was only the 74,3% of what it was in 2000, pinpointing a double-digit absolute change in this energy intensity, given the very high intensity this sector showed at the beginning of the study period.

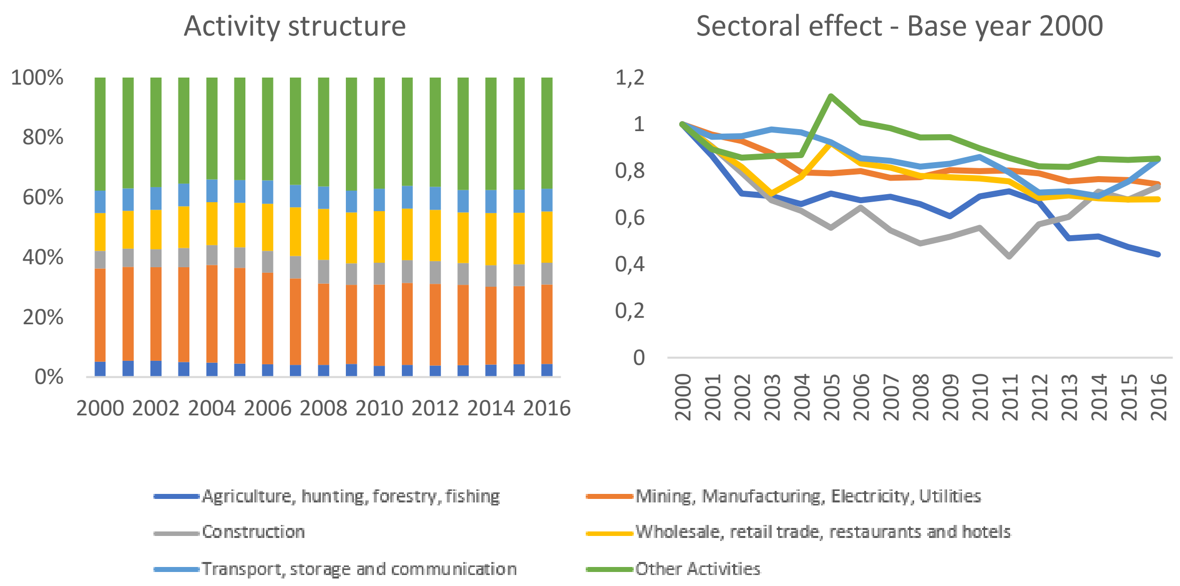

Figure 30 - Structural and sectoral effects for the Russian Federation. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

3.1.7 Results summary

In short, it can be said that all the considered countries managed to gain industrial energy intensity improvements in the period 2000-2016. It can be said that, in general, the countries achieving the most remarkable energy intensity improvements were those with the highest energy intensity values, with the notable exceptions of the UK, which achieved the largest percentage reduction, with its 2016 energy intensity being only the 61,4% of its 2000 level, and of India, which, despite very high initial levels of energy intensity, only managed to reduce its energy intensity up to the 78,5% of its 2000 level. Considering, however, that India ranked as the country with the second highest energy intensity among the considered ones, this reduction, in absolute terms, corresponds to 4 MJ/$. On the other hand, the Russian Federation, which is the country, among the studied ones, with the highest energy intensity levels, equal to 36,8 MJ/$, managed to achieve a percentage reduction comparable to that of the UK, with its 2016 energy intensity being equal to 24,1 MJ/$, i.e. 65,5% of its 2000 level. China, too, despite an initial increase in its energy intensity, obtained a fair reduction in its energy intensity values, down to the 74,7% of its 2000 level.

Figure 31 concretizes this country comparison.

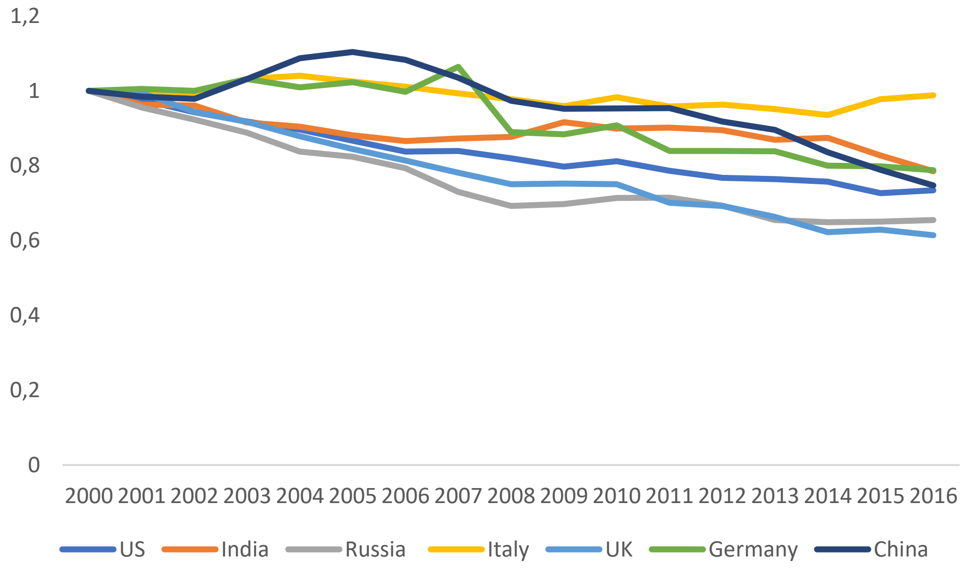

Figure 31 – Industrial energy intensity change by country, base year 2000. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

However, one fundamental point should not be disregarded, that is the energy use, in absolute terms. Indeed, by looking at Figure 32, it is evident how the US, despite an overall relatively contained value of their energy intensity, owed to their great value added numbers, were, until 2008 included, the world's largest consumers of energy, role which was later undertaken by China. Of remarkable importance is the persistent increase in the energy use of this latter country, similar, although to a much larger scale, to that observed for India after 2005. These are opposite to the declining trends observed in the three European economies and in the US.

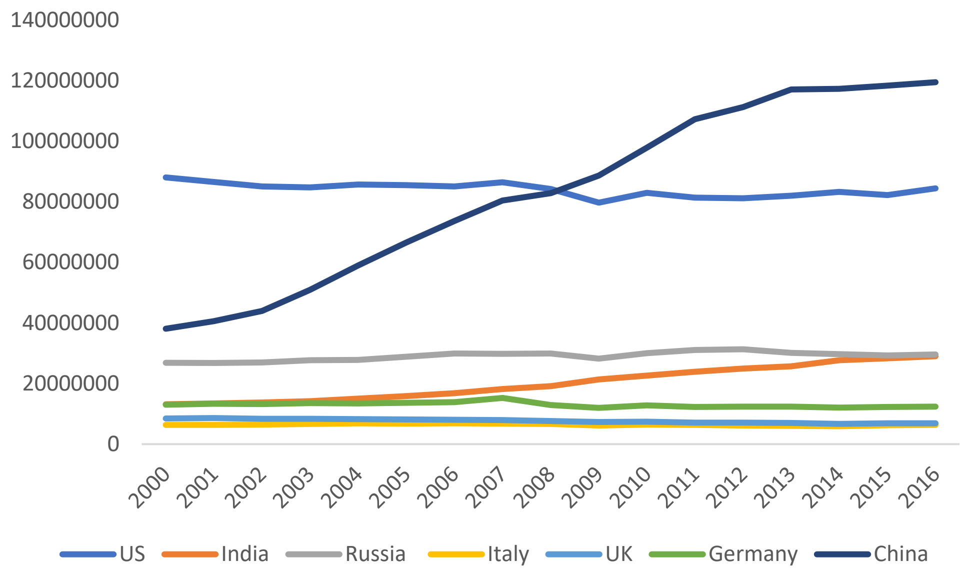

Figure 32 – Industrial energy use by country. Source: Author's own elaboration based on JRC WIOD data (2019).

One final remark should be made regarding a caveat intrinsic in the analysis carried in this Section. Indeed, as pointed out by Chirmiciu and Dosi (2011), the level of sectoral aggregation is quite high, and may lead to wrongly impute some changes to the sectoral rather than to the structural effect. As a matter of fact, for instance, the "Mining, Manufacturing, Electricity, Utilities" sector encloses both energy-intensive production, such as "Manufacture of basic metals" and the "Manufacture of coke and refined petroleum products", and less energy-intensive production, such as "Manufacture of basic pharmaceutical products and pharmaceutical preparations" and the "Manufacture of electrical equipment" (U.S. EIA, 2016). By doing so, all the structural shifts from a more energy-intensive manufacturing to a lesser one are disregarded, and are deemed as sectoral efficiency gains. For this reason, the results of the analysis performed in this Section should be considered with caution, by accounting for an inevitable underestimation of the structural effect, and an overestimation of the sectoral one.

3.1.8 An LMDI I decomposition of industrial energy consumption and Tapio decoupling analysis

In order to give an indication of the effect of the Great Recession on this specific driving factor, an LMDI I decomposition analysis of the change in the industrial energy consumption has been performed, for all the seven countries, with respect to the subperiods 2000-2007, 2008-2012 and 2013-2016. The driving factors used in this decomposition are the sectoral energy intensity, the structural change and the activity driver, i.e., the observed changes in the total value added.

In completion to this decomposition, a Tapio decoupling analysis has also been carried out to investigate the relationship between the industrial energy consumption and the indicator of economic activity used in this Chapter, namely the total value added, and how it changed across the full time window, other than in the three subperiods.

For the sake of brevity, the decomposition and decoupling results are reported in APPENDIX E. In the following, a discussion on the most interesting results is reported.

In order to review the decomposition analysis results, the studied countries can be clustered in two main groups, namely the developed economies, enclosing the first four countries, and the emerging ones, enclosing the last three. All the countries belonging to the former group displayed, during the crisis subperiod, a decrease in their energy consumption, suggesting negative repercussions of the Great Recession on the industrial consumption of energy. This decline has been driven, in all countries but Italy and Germany, by the contribution of the sectoral energy intensities and the structural drivers. On the other hand, the decline in Italy has been driven by the structural and activity drivers, whereas the one observed in Germany was entirely imputed to the negative contribution of the sectoral driver. The positive contribution of the activity driver in the crisis subperiod for the UK may appear at odds with what observed in the Section 2.3.2. However, it should be pointed out that, while in Chapter 2 the GDP per capita was used as a reference for the economic activity of a country, in this Chapter the total value added is used instead. Indeed, while GDP per capita in the UK has been declining between 2008 and 2012, the value added did increase in the same period, implying a different contribution sign in the two decomposition analyses performed. This is because, while GDP increased in those years, population did so at a higher rate, implying a lower GDP per capita in 2012 with respect to 2008.

The three emerging economies analysed, on the other hand, displayed increasing energy consumption for all the subperiods, with the sole exception of the Russian Federation's 2013-2016 subperiod, showing a mild two percent decrease in the energy consumption, most likely linked to the crisis experienced by this Country in those years. In this sense, as highlighted in the previous Chapter, at this level of analysis, it appears that the energy consumption of the emerging economies has been virtually unaffected by the Great Recession.

However, taking a closer look by means of the Tapio decoupling analysis, the relationship between the industrial energy consumption and the indicator of economic activity used has changed throughout the analysed time window, and the Great Recession may have played a role in this sense.

One general conclusion which can be drawn is that all countries, except the Russian Federation, managed to achieve a decoupling state between the "environmental pressure", namely industrial energy consumption, and the economic development variable, namely total value added, in the last considered subperiod, i.e., 2013-2016. In the case of Germany and the UK the decoupling state obtained has been absolute, or "strong", while for the US, China and India it has been relative, or "weak". Italy, on the other hand, achieved an expansive negative decoupling state, meaning that its energy consumption and value added both increased, but with the former doing so at a higher rate.

The Great Recession subperiod, however, showed a more diversified picture. Indeed, on the one hand the ***UK***, the ***US*** and ***Germany*** already achieved an absolute decoupling relationship in the 2008-2012 subperiod (i.e. strong decoupling), with the first two exhibiting this same relationship in the first considered subperiod, and the last evolving from an "expansive negative decoupling" state experienced in 2000-2007. On the other hand, ***China*** and ***India*** showed an expansive coupling state in the Great Recession subperiod, meaning that both the energy consumption and the value added increased, at approximately the same rate. This state has also been observed for China in the 2000-2007 subperiod, while in India, in the same subperiod, the relationship was one of relative decoupling (i.e. weak decoupling), given that the value added increased at a higher rate than the energy consumption.

The case of ***Italy*** stands for itself, as it evolved from "expansive coupling" in the 2000-2007 subperiod, to "recessive decoupling" in the Great Recession subperiod, meaning that both the energy consumption and the value added decreased as a result of the crisis, with the former doing so at a higher rate.

Lastly, the ***Russian Federation*** displayed "weak decoupling", "expansive coupling" and "recessive coupling" (i.e. both energy consumption and value added decreased, at approximately the same rate) states in the subperiods 2000-2007, 2008-2012 and 2013-2016, respectively. This is because, in 2000-2007, as mentioned in the previous Chapter, the Russian economy underwent a significant recovery process, and, even if energy consumption did increase, it did at a much slower rate than the value added. However, in the following subperiod, the two growth rates became approximately the same, to then get to a degrowth, again at similar rates, in the 2013-2016 subperiod, characterized by the Russian financial crisis of 2014-2015, the Russian ruble devaluation, and the oil price crisis.

By the way, when considering the full 2000-2016 time window, all the countries exhibit a decoupling state, with it being absolute, or strong, for Germany, the UK and the US, and relative, or weak, for all the remaining countries.

To conclude, it appears that, in the case of industrial energy consumption, the developed economies of Germany, the UK and the US obtained absolute decoupling with the total value added. However, the Great Recession seemingly weakened this decoupling relationship for the US, which evolved to a relative decoupling state in the last considered subperiod. This might be because energy consumption declined a lot in the years of the crisis with respect to 2000 values, and the slight recovery that followed caused the growth rate of this variable to turn to positive, although still smaller than the one of the value added. This is different from what has been observed in the previous Chapter, when considering the decoupling relationship between carbon dioxide emissions and GDP per capita.

Another observed difference is for the case of Italy, which, unlike what has been observed for the CO_2 emissions, did not obtain absolute decoupling in the last considered subperiod, due to a much smaller growth rate in its economic development than in its energy consumption, after the decline experienced in both variables in the years 2008-2012. The decoupling relationship between energy consumption and economic development is different from the one of CO_2 emissions also for China and India. As a matter of fact, the situation appears to be slightly more encouraging in the case of the former variables, even if the relationship observed in the respective last subperiods is represented by the same decoupling state, namely relative, or weak, decoupling. Lastly, the decoupling states for the Russian Federation are the same of those observed for the total carbon dioxide emissions, except for the last one, which is now “recessive coupling” instead of decoupling.

3.2. Carbon intensity of energy

As already pointed out, the carbon intensity of energy can be defined as the ratio of CO_2 emissions over the total primary energy supply for a certain country at a certain time or, equivalently, as the emissions per unit of energy. In this sense, it can be written as (Xu and Ang, 2013; Chen et al., 2013; Meng et al., 2018):

$$C_i = \sum_i \sum_j \frac{E_{ij}}{E_i} \frac{C_{ij}}{E_{ij}}$$

Where, the ratio $\frac{E_{ij}}{E_i}$ stands for the share of energy consumption of fuel *j* in area *i* over the total energy consumption of area i, and the ratio $\frac{C_{ij}}{E_{ij}}$ is the carbon emission coefficient, or the carbon emissions per unit of fuel *j* in area *i*.

The second factor, as observed by Chen et al. (2013), does not change much in the short term, and therefore will not be used in this analysis as its contribution to the emissions' change in this 27-years time window can be disregarded. To merely give an idea of the carbon emission coefficients of some fossil fuels, Table F.1 in the APPENDIX F reports the estimates made by Meng et al. (2018), based on the IPCC 2006 guidelines for national greenhouse gas inventories.

Conversely, the first factor, namely the relative share of each fossil fuel over the total energy use for a certain country, is of more interest and the following Section is entirely devoted to the analysis of the fuel mix evolution for the seven countries considered in the time window between 1990 and 2017.

For this purpose, data on primary energy consumption by fuel type, expressed in Million tonnes of oil equivalent (Mtoe) have been retrieved from the BP Statistical Review of World Energy (2019), relatively to the years between 1990 and 2017. This same database has been used by Olivier et al. (2020) to perform a similar analysis to the one pursued in this Section.

3.2.1 Changes in the fuel mix

3.2.1.1 Germany, United Kingdom and Italy

Germany

Germany is Europe's largest coal producer, with the highest coal-fired power generation (Olivier et al., 2016). Indeed, Figure 33 depicts a fuel mix still significantly reliant on coal, even if to declining extent, going from a 37% share on primary energy consumption in 1990 to 21% in 2017.[19] Another big contribution, which did not show such a pronounced decrease, is offered by oil, whose use even experienced an increase in the years preceding the new Century. One noteworthy change has also been observed for nuclear energy, which declined remarkably accordingly with the German government decision to shut down eight of its seventeen reactors following the Fukushima disaster of 2011. Lastly, the reliance on less carbon-intensive energy

[19] All numbers and percentages cited in Section 3.2.1 are based on the Author's own elaboration of BP Stats data (2019).

sources, such as natural gas and renewables, increased a lot, in accordance with Germany's pledge to reduce its emissions and coal reliance. However, in 2018 natural gas consumption decreased in Germany (Olivier and Peters, 2020). Next, the energy share represented by hydroelectricity remained approximately constant throughout the entire period, most likely due to physical and geographical limitations on the utilization of such energy source, that render Germany's hydropower capacity mature and already almost completely exploited (Spänhoff, 2014). But it is on other renewable energy sources, namely solar, wind, geothermal and biomass, that Germany experienced a massive increase, with their share on primary energy consumption ranging from 0,95% in 2000 to 13,29% in 2017.

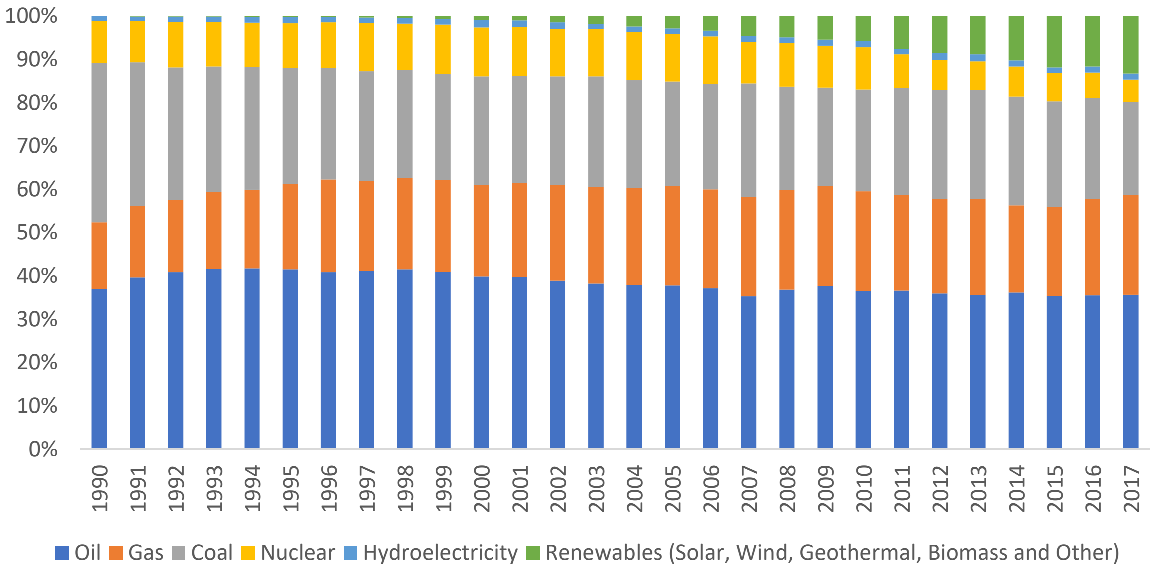

Figure 33 - Germany's fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

United Kingdom

The most notable change in the UK's fuel mix is the phasing out of coal, whose share on primary energy consumption went from 30% in 1990 to 5% in 2017, accounting for a total 86% decline in the twenty-seven-year time window (Figure 34). This is in line with the decarbonization process the UK has gone through, made explicit by their Clean Air Acts of 1956 and 1968, and its Climate Change Act of 2008, and by the UK's commitment to a phasing-out of its coal-fired power plants by 2025 (Olivier et al., 2016). This decrease has been compensated for by an increased reliance on natural gas and renewables, whereas the contribution of oil, nuclear and hydroelectricity remained approximately constant throughout the analysed time window. In 2016, the reliance on gas spiked, due to lower gas price in the UK (Olivier et al., 2016), continuing to increase even in 2018 (Olivier and Peters, 2020).

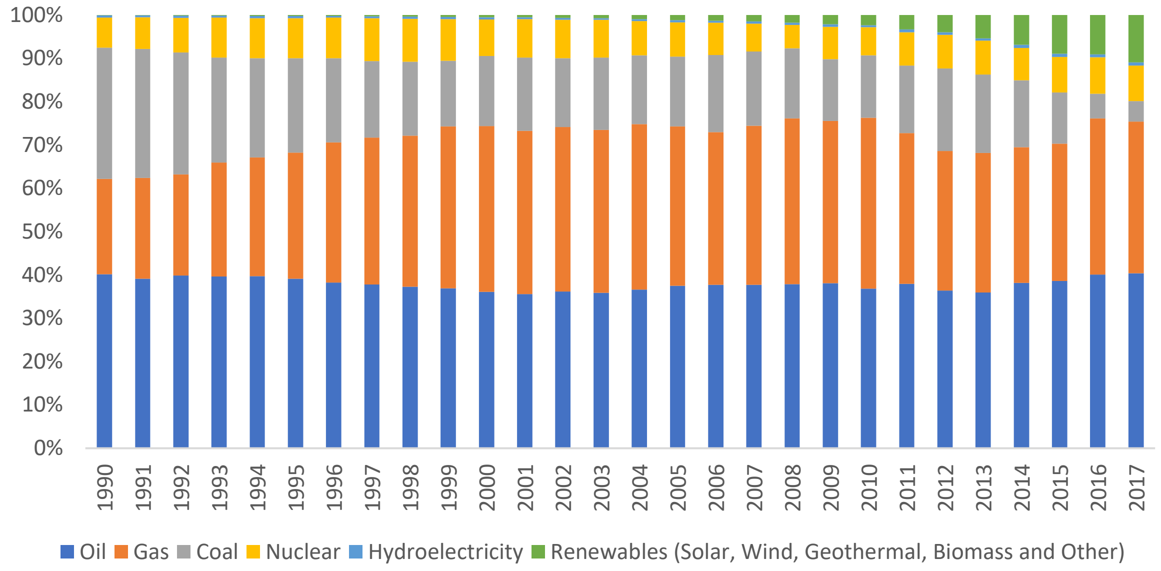

Figure 34 - UK's fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

Italy

Italy’s fuel fix has been, over the analysed time period, largely reliant on oil and gas, with the first declining 35% in the twenty-seven years considered, and the latter increasing by 58% over the entire period (Figure 35), with the increase experienced in the last two years analysed imputable, according to Olivier et al. (2016) to larger use of summer air-conditioning, although natural gas consumption in Italy declined by 3.3% in 2018 (Olivier and Peters, 2020). Unlike its two European counterparts, Italy’s fuel mix is not skewed towards coal, whose share over primary energy consumption was already as low as 9% at the beginning of the study period. Furthermore, Italy does not rely on nuclear power, given the shutdown of nuclear power plants in its territory, sealed by the Italian nuclear power referendum of 1987. Moreover, the Italian share of hydroelectricity is higher than for its European counterparts, given its larger geographical predisposition, although the potential is estimated to be already exploited at its 90% (Eni Scuola, 2012). Lastly, the share of the other renewables, just like it has been observed for the two other countries, experienced a major spike after the beginning of the new Century.

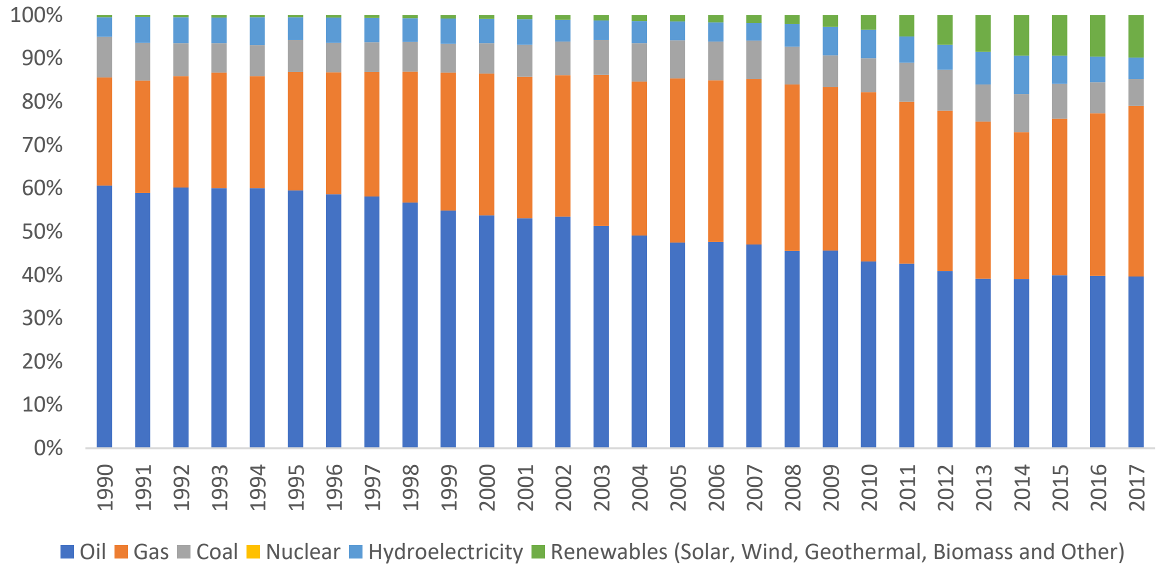

Figure 35 - Italy's fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

3.2.1.2 United States

The US fuel mix is largely based on oil and gas, accounting for, respectively, 41% and 29% of the US primary energy consumption in 2017 (Figure 36). Indeed, in 2015, according to Olivier and Peters (2016) the US had the largest share of natural gas consumption, and of global oil consumption. For what concerns coal, the US too decreased their reliance on this fossil fuel across the twenty-seven years of analysed data, with a total 28% reduction over the entire period, which may have been aided also by the setting, in 2015, of the new National Ambient Air Quality Standards (EPA, 2020). This decrease is ongoing, as, in 2018, half of the world's coal plants' retirements have been achieved in the US (Olivier et al., 2020). However, this phasing-out process had to be compensated for by an increased reliance on gas in the US, as the shares of oil, nuclear and hydroelectricity remained overall constant throughout the entire period, while the renewables share did not show the same pronounced increase that has been observed for the EU countries, reaching in 2017 only the 4% of the Country's energy consumption. This percentage is very close to the one of hydroelectricity, which, in 2017, represented the 3% of the US primary energy consumption. Indeed, as of 2016, the US were the third country in the world in terms of hydropower capacity (Olivier and Peters, 2016). Furthermore, in the same year, the US have been the world's first producers of nuclear energy in absolute terms, with this fuel representing, in 2017, the 9% of the US primary energy consumption. This has been aided also by the setting of the US-EPA Clean Power Plan of 2014, requiring the emissions produced by power plants to be reduced 25% with respect to 2005 levels by 2020 (Olivier and Peters, 2016).

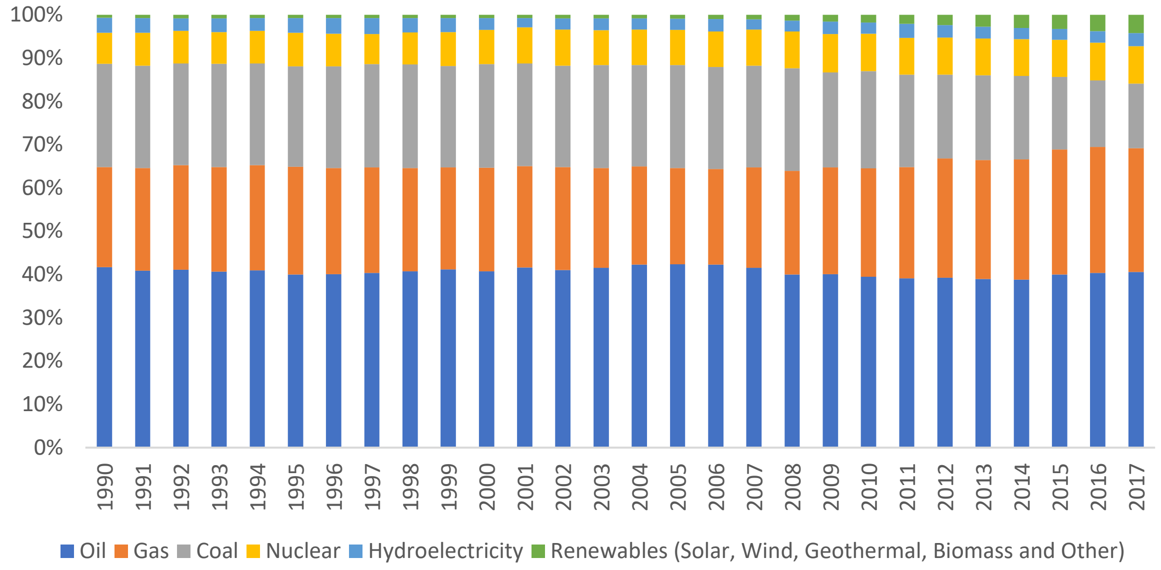

Figure 36 - US' fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

3.2.1.3 China

The fuel mix of China is dramatically skewed towards the use of coal, which, as of 2017, still represented the 60% of its energy consumption (Figure 37). Despite this high relevance of coal in China's fuel mix, it should still be noted that this figure is lower than the 77% observed at the beginning of the study period, which suggests an ongoing shift towards cleaner energy sources. This fact, however, should be coupled with an acknowledgement of the persistently increasing energy consumption in China, as, even if the share of coal on the total fuel mix is indeed lower, coal consumption levels of 2017 are about 258% higher than those of 1990, with China's coal consumption being half of the world's total in 2018 (Olivier et al., 2020). The decreased share of coal had to be compensated for by an increasing reliance on gas, whose share of 7% in 2017 is still way lower than the ones observed for the previous analysed countries; on nuclear, which has been sought as an alternative to coal, especially after the publication of the Energy Development Strategy Action Plan, 2014-2020, which imposed to cut the reliance on coal, in favour of cleaner technologies (World Nuclear Association, 2020); on hydroelectricity, for which China ranked as the first world hydropower country in terms of capacity in 2015 (Olivier and Peters, 2016); and on renewables, which experienced the most remarkable increase in their share in the years following 2010, owed to a very large growth in wind and solar power

(Olivier et al., 2020). The share of oil, after a spike experienced in the years around the beginning of the Century, went back to the same numbers observed at the beginning of the study period, although the same share corresponded to a value 433% higher.

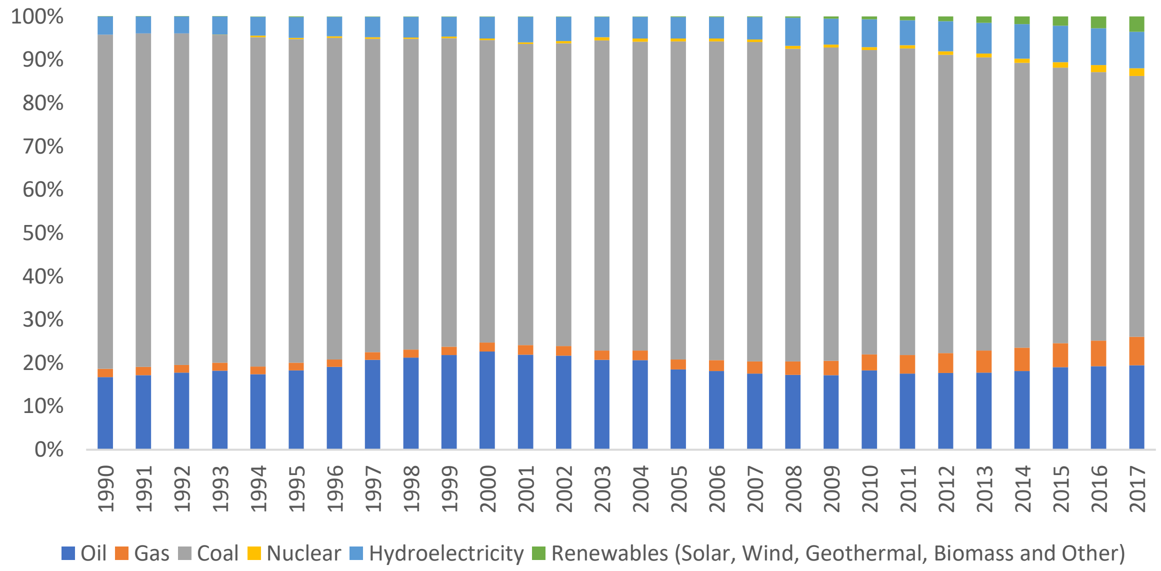

Figure 37 - China's fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

3.2.1.4 India

Similarly to China's, India's fuel mix is skewed towards coal, representing, in 2017, the 55% of the primary energy consumption of this Country (Figure 38). In this case, however, this share did not experience a significant decrease throughout the analysed time window, as the corresponding figure for the beginning of the period was 56%. The same reasoning holds true for oil, nuclear and gas. Indeed, the only significant changes occurred in the shares of hydropower, which declined from 8% to 4% in, respectively, 1990 and 2017, and of renewables, whose share experienced mild increases especially after 2007, reaching, in 2017, a 2,9% relevance, given the Indian Ministry for Energy commitment to increase by 175 GW renewable energy by 2021 (Olivier and Peters, 2016). These not so encouraging changes observed in the fuel mix of India are the reason behind the positive pressure exerted by the carbon intensity of energy factor on CO_2 emissions for the four subperiods considered in Section 2.3.

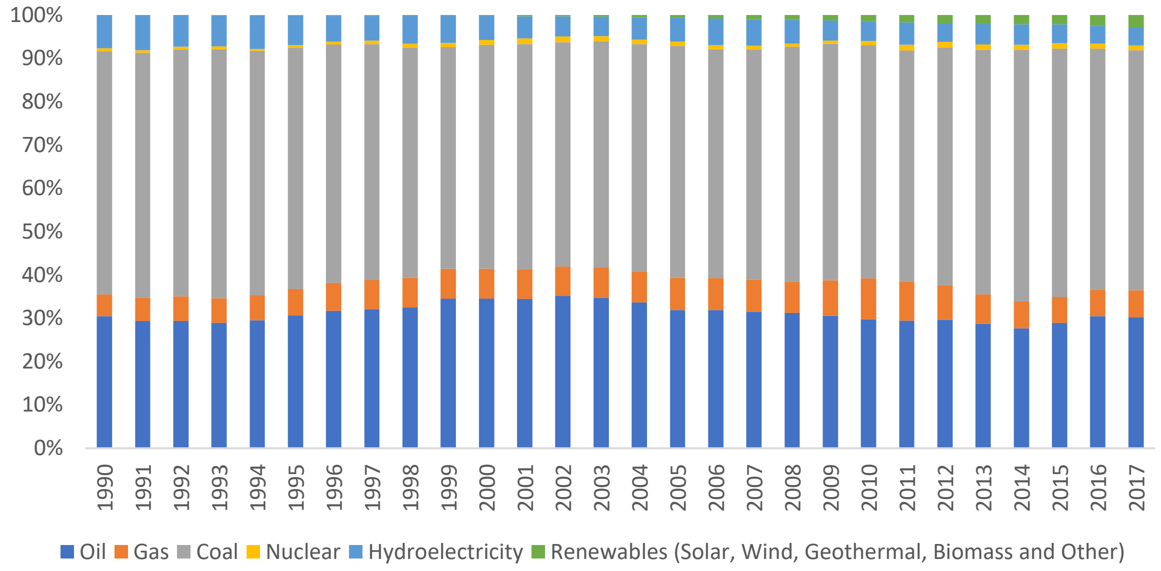

Figure 38 - India's fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

3.2.1.5 Russian Federation

About 53% of the Russian Federation's energy consumption in 2017 was represented by gas, followed by oil (22%) and coal (12%). At the beginning of the study period, the ranking order was the same, although with different shares, being 41%, 30% and 21%, respectively, for gas, oil and coal (Figure 39). This means that the Russian Federation increased its reliance on gas at the expense of oil and coal, with the latter decreasing by 54% in the twenty-seven years of data analysed. Moreover, while the share of energy consumption covered by hydroelectricity increased throughout the analysed period, going from 4% in 1990 to 6% in 2017, the share of renewables, which is negligible, did not show any significant increase in the twenty-seven years of data analysed. Indeed, as stated by Olivier et al. (2020), the Russian Federation is the only country, among the top emitters, which virtually did not make use of wind and solar power, and of biofuels for road transport. Lastly, the share represented by nuclear energy went from 3% in 1990 to 7% in 2017.

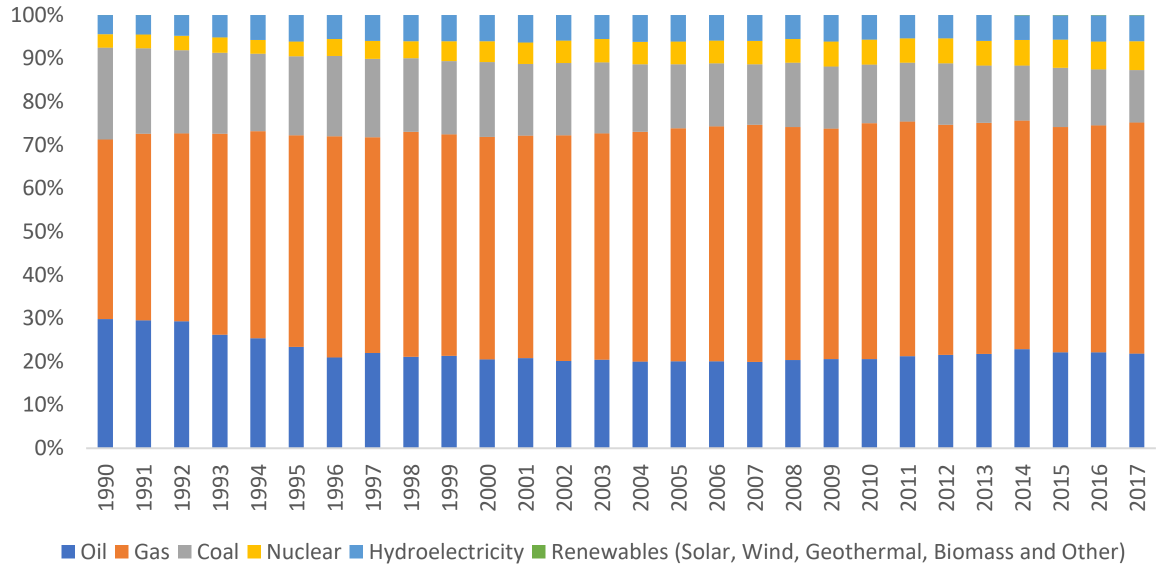

Figure 39 - Russian Federation's fuel mix evolution, years 1990-2017. Source: Author's own elaboration based on BP Stats data (2019).

3.2.1.6 Summary of results

Summing up, in general, all the analysed countries have been shifting towards less carbon-intensive fuel mixes. The most remarkable changes have been observed for the developed economies, which displayed, nevertheless, significantly lower shares of coal with respect to the developing economies, with the exception of the ***Russian Federation***, which showed a fuel mix much more skewed towards gas. ***China*** and ***India***, the two countries which displayed the highest reliance on coal, still accounting for more than half of their energy consumption in 2017, showed differing situations, with the former significantly decreasing their reliance on this fossil fuel relatively to the others, and the latter not experiencing significant changes in its share over the entire time window analysed.

Despite the observed general shift away from coal, traditional fossil fuels (i.e. coal, oil, gas) still represent the majority of energy consumption for all the considered economies, with low-carbon energy sources, such as nuclear, hydro, and other renewables still representing a minority, with the European economies considered standing out as the best performers in this sense. This may be linked to the European commitments embodied in regulations such as the 2009/28/EC Renewable Directive, which sets the so-called 20-20-20 goal, that aims, among other things, at a 20% of energy at the overall EU level to be provided by RES by 2020 (Vigotti, 2015), or as the more ambitious Energy Roadmap 2050, that aims for carbon neutrality at the EU level by the self-titled year (Imperial College London et al., 2014).

3.2.2 The role of renewables

When targeting climate change and the improvement of a country's fuel mix, it behoves to make a mention of renewable energy sources (RES). Indeed, the array of benefits offered by this kind of energy sources is outstanding. These are, to name a few, their contribution to the decarbonization of the fuel mixes; their contribution to the reduction of the need for fossil fuel imports, contributing to a higher energy independence (World Energy Council, 2016), and their overall huge energy potential, considering that, for instance, solar energy alone uses a resource that would be more than enough to cover all of the world energy's demand. In addition to that, this kind of energy source does not entail security and military risks, as does, for example nuclear power (Zahedi, 2011). Lastly, they could contribute to the creation of new jobs, hence increasing employment rates (World Energy Council, 2016).

Even if the benefits from RES deployment are undeniable, their implementation, while increasing, is still small compared to more carbon-intensive fossil fuels, as further underlined in the previous Section. Indeed, while the global installed RES capacity has more than tripled between 2000 and 2019, with this increase primarily driven by wind and solar power expansion in the years following 2009, and RES accounting for about 60% of the total new capacity additions (World Energy Council, 2016), the share of global TPES provided by RES, despite minor improvements experienced mainly in the "Wind, solar, etc." and "Hydro" categories, is still marginal, ranging at an approximate 10% level (Figure 40).

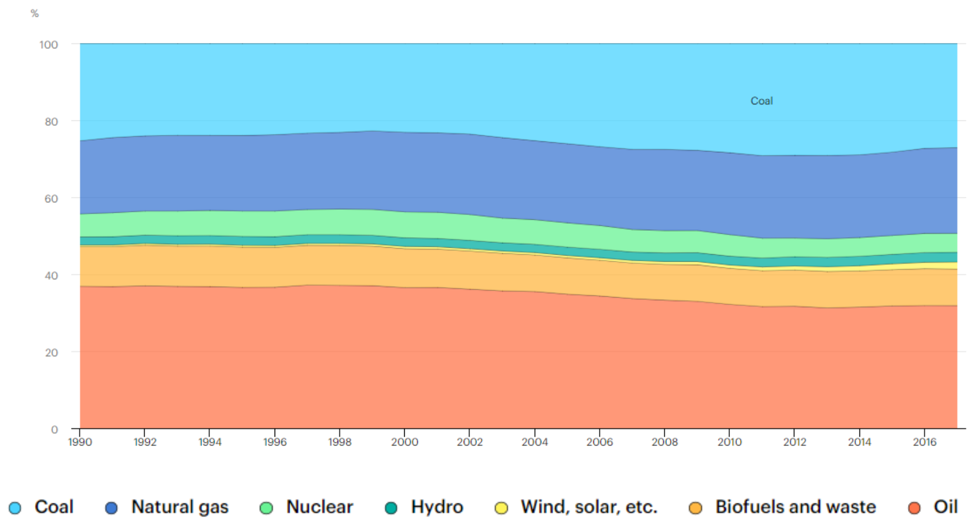

Figure 40 - Total Primary Energy Supply by source, in percentage, years 1990-2017. Source: IEA, 2019b.

This is because, indeed, there are some peculiar characteristics of RES that hinder their smooth integration in energy and electricity systems worldwide. More specifically, there are two main types of RES: dispatchable and non-dispatchable (IEA-ETSAP and IRENA, 2015). The first category includes all those RES, such as hydro, biomass and geothermal power, that can be deployed following demand and dispatched on request of power grid operators, just like the traditional primary energy sources (e.g. coal, oil). All of the above cannot be done with non-dispatchable RES, or Variable Renewable Energy (VRE) sources, that include, for instance, wind, solar photovoltaic and ocean power. In fact, there are peculiar characteristics to this kind of RES that hinder their normal utilization as energy sources, that are:

- *Non-controllable variability*, owed to the fact that the output from this kind of energy sources changes over time, in a way that cannot be controlled, as it is caused by nature-driven weather conditions;
- *Partial unpredictability*, that is to be ascribed to the errors made in forecasts of VRE availability, that are unavoidable, given the uncertainty of changes of said resources;
- *Location dependence*, related to the fact that VRE availability is conditional on the geographical proximity to resources;
- *Modularity*, meaning that a production site for VRE has a much lower scale than a traditional one, requiring a larger number of sites to obtain the same amount of energy;
- *Low short-term marginal costs*, that are close to zero.

The concurrence of all these peculiarities is what poses challenges to the introduction of VRE into the energy and power systems around the world (IEA-ETSAP, IRENA, 2015; Cretì, Fontini, 2019; Philibert, 2018).

Despite the development of several possible solutions easing the utilization of renewables proposed by the literature, the current use of this kind of energy sources remains quite small. Nevertheless, the EIA's International Energy Outlook of 2019 depicts a very optimistic picture, especially in the field of electricity generation. Indeed, it projects renewables to collectively increase to 49% of global electricity generation by 2050, with solar showing the fastest growth and hydro showing the slowest, due to physical constraints related to this source.

In the short term, however, the Covid-19 outbreak-caused delays in construction activity due to supply chain disruptions, lockdown measures, social-distancing guidelines and emerging financing challenges, may cause, as predicted by IEA (2020), the first downward trend to be observed since 2000 in renewable electricity capacity. Nevertheless, the majority of these delayed projects are expected to be implemented in 2021 and lead to a rebound in capacity additions, so as to reach, in 2021, approximately the same level of renewable capacity additions of 2019. Despite the rebound, the combined growth in 2020 and 2021 remains below the one accounted for by previous forecasts, showing that, indeed, the current crisis also displays its impact in the field of renewables integration.

FINAL REMARKS

This work operated a LMDI I decomposition analysis of the change in energy-related CO_2 emissions for the years 1990-2017 for Germany, United Kingdom, Italy, United States, China, India and the Russian Federation. Furthermore, in order to investigate more in detail the effects of the Great Recession on emissions, a Tapio decoupling analysis was carried out, which allowed to shed a light on the changing relationship between the energy-related CO_2 emissions and one of its drivers, namely GDP per capita.

Exception made for China and India, all the analysed countries managed to reduce their emissions in the study period. When considering the four drivers of emissions advocated by Kaya, namely population, GDP per capita, energy intensity of GDP and carbon intensity of energy, in general, the main positive driving factor has been the GDP per capita, whereas the main negative driving factor has been the energy intensity of GDP. This statement is true for all countries but the Russian Federation, where the energy intensity driver exerted a positive contribution in all subperiods analysed but the 2000-2007 one, and the GDP per capita exerted a negative contribution in the 1990-1999 subperiod, due to repercussions of the Soviet Union fall, and in the last subperiod, i.e., 2013-2017, due to the Russian financial crisis.

Another general statement which can be made is that the developed economies, namely ***Germany***, the ***UK***, the ***US*** and, to a lower extent, ***Italy***, have succeeded in the reduction of their emissions, accompanied by a generally good degree of economic growth. On the other hand, the emerging economies of ***China*** and ***India*** experienced a huge economic development, coupled, however, with an equally important growth in their emissions, with China, however, reducing its growth rate remarkably in the last subperiod considered. Lastly, the ***Russian Federation*** underwent a recovery process from the Soviet Union fall-induced economic shock, which brought up a massive drop in its emissions that, despite the economic recovery, managed to stabilize and not spike back up again.

As for the link between emissions and the economic downturn experienced during the Great Recession, the Tapio decoupling analysis provides some interesting insights. The most visible impacts of the downturn have been observed in ***Italy*** and the ***UK***. Indeed, these two countries experienced a "recessive decoupling" between their CO_2 emissions and GDP per capita during the period 2008-2012 (i.e. both quantities declined over this period, but the former did so at a faster rate) followed by an absolute decoupling in the period 2013-2017. This seems to suggest that the economic recovery did not come at the expense of the environment, as, while the economy grew, emissions continued to decline.

Even if not linked to the Great Recession, a similar recovery process has also been observed in the ***Russian Federation***, where, after the period following the Soviet Union fall, namely 1990-1999, characterized by a "recessive coupling" relationship between the two considered variables (i.e. both variables declined, at approximately the same rate), the relationship turned to one of relative decoupling in the years 2000-2007. It remains to be assessed whether this Country will succeed in maintaining this kind of recovery process even after the crisis it experienced in the last subperiod, namely, 2013-2017.

Such straightforward effects of the crisis have not been observed for the remainder of the countries. Indeed, on the one hand, ***Germany*** and the ***US*** maintained an absolute decoupling relationship in the subperiods before, during, and after the Great Recession's one. The only visible effect has been a mere reduction in the value of the decoupling elasticities in the last subperiod, which seems to point to a lower order of magnitude, although of opposite sign, of the percentage variation in emissions with respect to the one of the economic driver. On the other hand, ***China*** and ***India*** improved their decoupling relationship, going from "expansive coupling" (i.e. both variables increased, at approximately the same rate) and "expansive negative decoupling" (i.e. both variables increased, but emissions did so at a faster rate) in the subperiods before and during the Great Recession to one of relative decoupling in the subperiod 2013-2017.

In order to more deeply understand the drivers behind the energy-related CO_2 emissions, a Fisher Ideal index decomposition has also been carried out for the energy intensity of GDP driver, by decomposing the industrial energy intensity of the seven countries into the sectoral driver, namely energy intensity changes within sectors, and the structural driver, namely economy's shifts towards less energy-intensive sectors. Hence, the evolution of the three variables has been studied for the period 2000-2016.

It turned out that, in all the considered countries, the industrial energy intensity has improved throughout the entire study period. A few countries, namely the ***UK*** and the ***Russian Federation***, displayed an approximately equal contribution to this reduction exerted by the two effects. However, energy intensity improvements of ***Germany***, the ***US***, ***China*** and ***India*** have been caused, in full, by the sectoral effect, while those of ***Italy*** have been caused entirely by the structural effect.

Following this results, referring to the same time window, a LMDI I decomposition and a Tapio decoupling analysis have been performed relatively to the change in the industrial energy consumption, subdivided into three driving factors: sectoral energy intensities, structural change and activity, pinpointed by the change in the total value added. The main result is that the only country displaying a visible impact of the Great Recession, ***Italy***, showed a "recessive decoupling" relationship between industrial energy consumption in the period 2008-2012, followed by an "expansive negative decoupling" in the period 2013-2017. This points to a recovery process which has been faster in the energy consumption than in the economic rebound, unlike what happened in the case of CO_2 emissions. The other countries did not seemingly show such a straightforward effect of the crisis subperiod.

On the one hand, the developed economies of ***Germany*** and the ***UK*** achieved absolute decoupling in the subperiods during and after the Great Recession. The ***US***, however, evolved from an absolute decoupling relationship before and during the Great Recession to one of relative decoupling in the subperiod 2013-2017, suggesting that the industrial energy consumption has been increasing in the last years considered, but not as fast as the US economy. On the other hand, the developing economies of ***China*** and ***India*** improved their decoupling state from one of "expansive coupling" during the Great Recession subperiod, to one of relative decoupling in the last subperiod. Finally, the ***Russian Federation*** displayed, except for the last subperiod, the same decoupling states already observed for the emissions.

The last driving factor analysed is the carbon intensity of energy, through a commentary on the evolution of the fuel mix of the primary energy consumption. From this analysis, it turned out that all the studied countries improved their fuel mixes during the study period, even if the traditional fossil fuels, namely coal, oil and gas, still represent the majority of primary energy consumption. In particular, coal, the most carbon-intensive among the energy sources considered, is still accounting for more than half of primary energy consumption in China and India. Finally, the three European economies have proved to be particularly well performing in terms of renewables (including hydroelectricity) implementation, with the highest share in 2017 recorded in Italy, with a 14,8% of its energy consumption covered by hydropower and other renewables (i.e. solar, wind, biomass, geothermal and other).

One last remark is that, as mentioned in the Introduction, the Covid-19 outbreak-induced crisis is likely to have an impact on emissions similar, if not greater, than the Great Recession. Hence, future research could apply an analysis similar to the one conducted in this work to infer the effect of the current crisis on emissions and their drivers. Indeed, the lack of data availability precluded the possibility to pursue it in this work.

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APPENDIX A: mathematical specification of the main IDA techniques

First, let assume there is an energy- related aggregate *V*, with *n* contributing factors associated to it. Each of these *n* factors corresponds to a quantifiable variable *x* (Ang, 2005). Then, let *i* be a sub-category of the aggregate *V*, such that: $V_i = x_{1,i}x_{2,i} \dots x_{n,i}$. The general IDA identity will be given by:

$$V = \sum_i V_i = \sum_i x_{1,i}x_{2,i} \dots x_{n,i}$$

The changes in *V* from time 0 to time T can be expressed in two ways. In the multiplicative decomposition:

$$D_{tot} = \frac{V^T}{V^0} = D_{x_1}D_{x_2} \dots D_{x_n}$$

In the additive decomposition:

$$\Delta V_{tot} = V^T - V^0 = \Delta V_{x_1} + \Delta V_{x_2} + \cdots + \Delta V_{x_n}$$

A.1. The conventional Laspeyres index method

The Laspeyres index methodology, the most popular among the first IDA techniques proposed in the literature, can be used to decompose various energy-aggregate variables. In this case, the focus is on the decomposition of energy intensity into two driving factors. This Section is based on the survey review of main decomposition techniques presented by Ang and Zhang (2000).

When expressing aggregate energy intensity across all sectors as:

$$I_t = \sum_i S_{i,t}I_{i,t}$$

With: $S_{i,t}$ being the production share of sector *i* at time *t* and $I_{i,t}$ the energy intensity of sector *i* at time *t*.

Energy intensity decomposition, relying on the Laspeyres index method, is given by, for the multiplicative form:

$$D_{str} = \sum_i S_{i,T}I_{i,0} \,/ \sum_i S_{i,0}I_{i,0}$$

$$D_{int} = \sum_i S_{i,0} I_{i,T} / \sum_i S_{i,0} I_{i,0}$$

$$D_{rsd} = D_{tot}/(D_{str} D_{int})$$

Where, D are the decomposition terms, namely D_{str} stands for structural effect, while D_{int} stands for intensity effect. The term D_{rsd} is the residual, unexplained part of the decomposition analysis.

For the additive form:

$$\Delta I_{str} = \sum_i S_{i,T} I_{i,0} - \sum_i S_{i,0} I_{i,0}$$

$$\Delta I_{int} = \sum_i S_{i,0} I_{i,T} - \sum_i S_{i,0} I_{i,0}$$

$$\Delta I_{rsd} = \Delta I_{tot} - \Delta I_{str} - \Delta I_{int}$$

A.2. The LMDI I method

The mathematical formulation of the LMDI I method for the decomposition task referred to at the beginning of this Appendix is (Ang, 2005):

$$D_{x_k} = \exp(\sum_i \frac{L(V_i^T, V_i^0)}{L(V^T, V^0)} \ln (\frac{x_{k,i}^T}{x_{k,i}^0})) = \exp(\sum_i \frac{(V_i^T - V_i^0) \big/ (lnV_i^T - lnV_i^0)}{(V^T - V^0) \big/ (lnV^T - lnV^0)} \times \ln (\frac{x_{k,i}^T}{x_{k,i}^0}))$$

$$\Delta V_{x_k} = \sum_i L(V_i^T, V_i^0) \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0}\right) = \sum_i \frac{V_i^T - V_i^0}{lnV_i^T - lnV_i^0} \ln (\frac{x_{k,i}^T}{x_{k,i}^0})$$

With *L (a, b) = (a - b) / (ln a – ln b)*, and D_{x_k} and ΔV_{x_k} being the decomposition factors relative to the characteristic x_k computed in the multiplicative and additive form, respectively.

A.3. The Fisher Ideal index method

The mathematical formulation of the Fisher Ideal index method for the decomposition task referred to at the beginning of this Appendix is, when there are only two factors x_1 and x_2:

$$D_{x_k} = \sqrt{D^L_{x_k} D^P_{x_k}} \qquad k = 1,2$$

$$D_{tot} = D_{x_1} D_{x_2}$$

And:

$$D^L_{x_1} = \sum_i X^T_{1i} X^0_{2i} \,/\, \sum_i X^0_{1i} X^0_{2i} \qquad D^L_{x_2} = \sum_i X^0_{1i} X^T_{2i} \,/\, \sum_i X^0_{1i} X^0_{2i}$$

$$D^P_{x_1} = \sum_i X^T_{1i} X^T_{2i} \,/\, \sum_i X^0_{1i} X^T_{2i} \qquad D^P_{x_2} = \sum_i X^T_{1i} X^T_{2i} \,/\, \sum_i X^T_{1i} X^0_{2i}$$

With $D^L_{x_k}$ and $D^P_{x_k}$ being the Laspeyres and Paasche indices, respectively.

APPENDIX B: LMDI I decomposition

The numerical results of the decomposition analysis carried in Chapter 2.3 are summed up in Table B.1.

Table B.1 - LMDI I decomposition of the change in CO_2 emissions. Source: Authors' own elaboration based on IEA and UN Stats data (2019).

Country	Time period	Population effect	GDP per capita effect	Energy intensity effect	Carbon intensity effect	Cumulated change
Germany	1990-1999	22,426	120,0044	-183,939	-83,53999	-125,04831
	2000-2007	-4,519	78,3569	-92,892	-26,53681	-45,59010
	2008-2012	-3,187	22,1511	-66,977	17,50022	-30,51263
	2013-2017	18,252	45,2316	-79,358	-29,10065	-44,97512
UK	1990-1999	13,2342331	105,0343	-78,2527	-77,45691	-37,44113
	2000-2007	21,0993763	78,3895	-127,8761	29,55766	1,17043
	2008-2012	14,5151113	-11,6743	-38,8467	-10,44869	-46,45462
	2013-2017	11,9262174	22,8889	-67,9865	-55,10004	-88,27144
Italy	1990-1999	1,3987063	50,22210	4,239976	-27,54216	28,318629
	2000-2007	13,7391715	19,88424	-3,223785	-9,37515	21,024472
	2008-2012	7,2832873	-31,29150	-23,06554	-15,10350	-62,177255
	2013-2017	-0,5926817	12,92746	-16,48463	-11,94465	-16,094505
US	1990-1999	570,2	969,094	-795,843	17,34	760,792
	2000-2007	377,3	615,698	-835,328	-200,86	-43,159
	2008-2012	165,3	28,527	-498,672	-304,63	-609,503
	2013-2017	143,1	313,835	-523,325	-210,83	-277,222
China	1990-1999	244,528	2014,753	-1690,64	263,41	832,043
	2000-2007	196,168	3103,144	-465,04	539,25	3373,526
	2008-2012	149,787	2586,414	-663,41	77,70	2150,493
	2013-2017	195,096	2275,149	-1998,66	-404,15	67,433
India	1990-1999	117,2204	-117,22	232,2387	89,6957	321,9344
	2000-2007	120,5805	-120,58	269,2182	106,5843	375,8025
	2008-2012	83,6075	-83,61	379,4153	85,4249	464,8402
	2013-2017	92,8405	-92,84	248,4516	58,3306	306,7822

Russian Federation	1990-1999	-12,9796	-864,128	223,997	-67,4411	-720,551
	2000-2007	-39,4122	727,914	-564,333	-64,8376	59,331
	2008-2012	5,0859	58,587	25,695	-35,2557	54,111
	2013-2017	10,6529	-5,864	50,575	-87,0185	-31,654

APPENDIX C: Decoupling analysis

C.1 The Tapio's decoupling categories

The following table is based on the works of Tapio (2005), Liu et al. (2015) and Chen et al. (2018):

Table C.1 - Description of the eight decoupling states according to Tapio decomposition. Sources: Tapio (2005) and Chen et al. (2018).

States		Conditions required
Decoupling	Strong decoupling	$\Delta EP < 0$, $\Delta DF > 0$ $d < 0$
	Weak decoupling	$\Delta EP > 0$, $\Delta DF > 0$ $0 < d < 0.8$
	Recessive decoupling	$\Delta EP < 0$, $\Delta DF < 0$ $d > 1.2$
Negative decoupling	Expansive negative decoupling	$\Delta EP > 0$, $\Delta DF > 0$ $d > 1.2$
	Strong negative decoupling	$\Delta EP > 0$, $\Delta DF < 0$ $d < 0$
	Weak negative decoupling	$\Delta EP < 0$, $\Delta DF < 0$ $0 < d < 0.8$
Coupling	Expansive coupling	$\Delta EP > 0$, $\Delta DF > 0$ $0.8 < d < 1.2$
	Recessive coupling	$\Delta EP < 0$, $\Delta DF < 0$ $0.8 < d < 1.2$

C.2 Results of the Tapio's decoupling analysis

The numerical results of the decoupling analysis carried in Chapter 2.5 are summed up in Table C.2.

Table C.2 - Tapio decomposition results. Source: Authors' own elaboration based on IEA and UN Stats data (2019).

Country	1990-1999		2000-2007		2008-2012		2013-2017		1990-2017	
	d	Decoupling state	*d*	Decoupling state	*d*	Decoupling state	*d*	Decoupling state	*d*	Decoupling state
Germany	-0,906	Strong decoupling	-0,538	Strong decoupling	-1,331	Strong decoupling	-0,936	Strong decoupling	-0,528	Strong decoupling
UK	-0,311	Strong decoupling	0,014	Weak decoupling	3,84	Recessive decoupling	-3,364	Strong decoupling	-0,673	Strong decoupling
Italy	0,549	Weak decoupling	1,059	Expansive coupling	1,913	Recessive decoupling	-1,191	Strong decoupling	-1,291	Strong decoupling
US	0,769	Weak decoupling	-0,066	Strong decoupling	-20,106	Strong decoupling	-0,832	Strong decoupling	-0,018	Strong decoupling
China	0,318	Weak decoupling	1,124	Expansive coupling	0,807	Expansive coupling	0,026	Weak decoupling	0,381	Weak decoupling
India	1,546	Expansive negative decoupling	1,012	Expansive coupling	1,503	Expansive negative decoupling	0,583	Weak decoupling	1,283	Expansive negative decoupling
Russian Federation	0,867	Recessive coupling	0,065	Weak decoupling	0,922	Expansive coupling	5,353	Recessive decoupling	-1,318	Strong decoupling

APPENDIX D: Energy intensity decomposition analysis

D.1 Fisher Ideal index method formulae used

This Section is built on the work of Metcalf (2008).

In order to apply the Fisher Ideal index method, the Laspeyres and Paasche indices for the structural and sectoral effects in year *t* have to be constructed first:

$$L_t^{str} = \frac{\sum_i e_{i0} s_{it}}{\sum_i e_{i0} s_{i0}}$$

$$L_t^{sec} = \frac{e_{it} s_{i0}}{e_{i0} s_{i0}}$$

$$P_t^{str} = \frac{\sum_i e_{it} s_{it}}{\sum_i e_{it} s_{i0}}$$

$$P_t^{sec} = \frac{\sum_i e_{it} s_{it}}{\sum_i e_{i0} s_{it}}$$

Given the results obtained, the Fisher Ideal indices for the structural and sectoral effects in year *t* are:

$$F_t^{str} = \sqrt{L_t^{str} P_t^{str}}$$

$$F_t^{sec} = \sqrt{L_t^{sec} P_t^{sec}}$$

After defining the two Fisher Ideal indices, the aggregate energy intensity's decomposition between time 0 and time *t* is obtained from:

$$\frac{e_t}{e_0} = I_t = F_t^{str} F_t^{sec}$$

With e_0 being the energy intensity of the base year, namely 2000 in this context.

D.2 Sectors

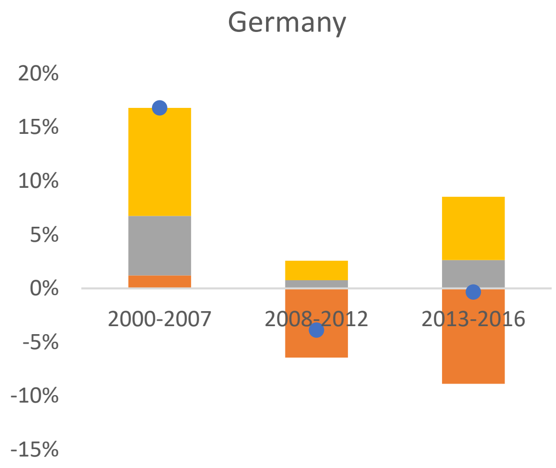
Table D.1 - Sectors' classification. Source: Author's own elaboration based on the classification of Corsatea et al., 2019 and UN Stats, 2019.

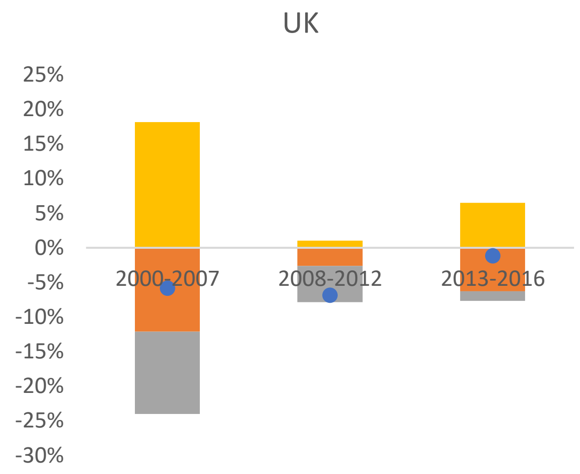
Description	Grouping category
Crop and animal production, hunting and related service activities	Agriculture, Forestry, Fishing
Forestry and logging	
Fishing and aquaculture	
Mining and quarrying	Mining, Manufacturing, Electricity, Utilities
Manufacture of food products, beverages and tobacco products	
Manufacture of textiles, wearing apparel and leather products	
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	
Manufacture of paper and paper products	
Printing and reproduction of recorded media	
Manufacture of coke and refined petroleum products	
Manufacture of chemicals and chemical products	
Manufacture of basic pharmaceutical products and pharmaceutical preparations	
Manufacture of rubber and plastic products	
Manufacture of other non-metallic mineral products	
Manufacture of basic metals	
Manufacture of fabricated metal products, except machinery and equipment	
Manufacture of computer, electronic and optical products	
Manufacture of electrical equipment	
Manufacture of machinery and equipment n.e.c.	
Manufacture of motor vehicles, trailers and semi-trailers	
Manufacture of other transport equipment	
Manufacture of furniture; other manufacturing	
Repair and installation of machinery and equipment	
Electricity, gas, steam and air conditioning supply	
Water collection, treatment and supply	
Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	
Construction	Construction
Wholesale and retail trade and repair of motor vehicles and motorcycles	Wholesale, retail trade, restaurants and hotels
Wholesale trade, except of motor vehicles and motorcycles	
Retail trade, except of motor vehicles and motorcycles	
Accommodation and food service activities	
Water transport	Transport, storage and communication
Air transport	
Warehousing and support activities for transportation	
Postal and courier activities	
Land transport and transport via pipelines	
Publishing activities	

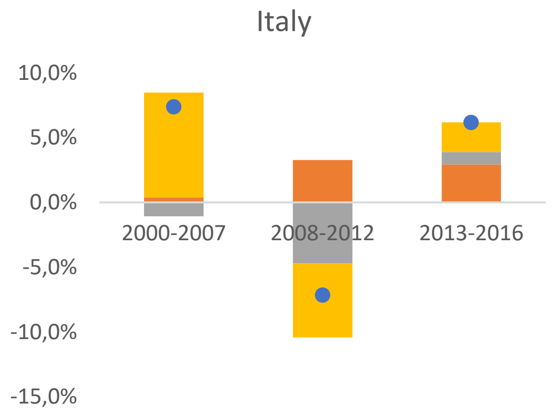
Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities Telecommunications	Transport, storage and communication
Computer programming, consultancy and related activities; information service activities Financial service activities, except insurance and pension funding Insurance, reinsurance and pension funding, except compulsory social security Activities auxiliary to financial services and insurance activities Real estate activities Legal and accounting activities; activities of head offices; management consultancy activities Architectural and engineering activities; technical testing and analysis Scientific research and development Advertising and market research Other professional, scientific and technical activities; veterinary activities Administrative and support service activities Public administration and defence; compulsory social security Education Human health and social work activities Other service activities Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use Activities of extraterritorial organizations and bodies	Other activities

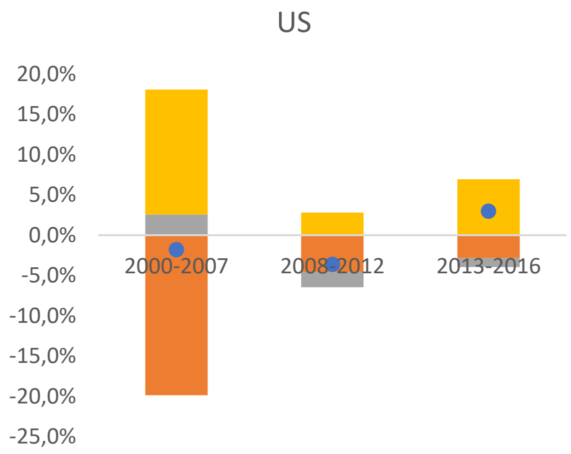
APPENDIX E: LMDI I decomposition and Tapio decoupling analysis for industrial energy consumption

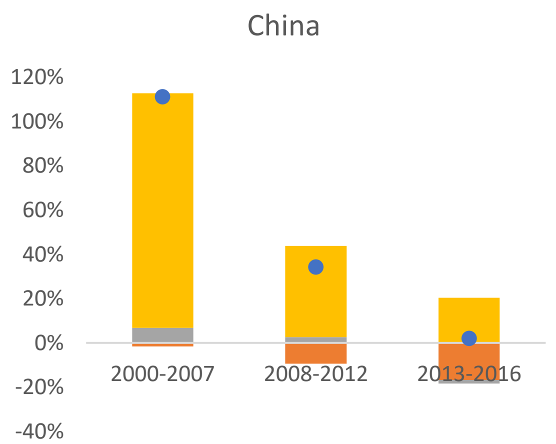
E.1 LMDI I decomposition

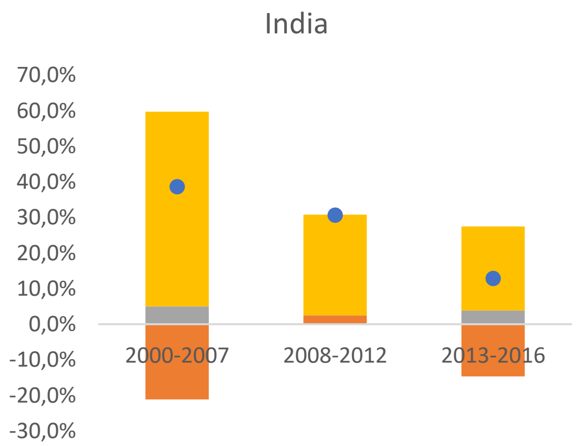












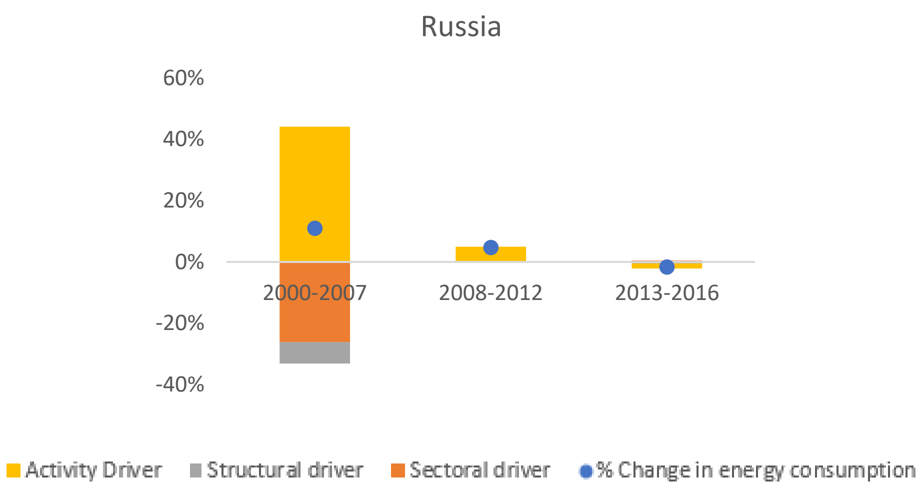


Figure E.1 - LMDI I decomposition of the change in industrial energy consumption. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

E.2 Tapio decoupling analysis

Table E.2 - Tapio decoupling analysis results. Source: Author's own elaboration based on JRC WIOD and UN Stats data (2019).

Country	2000-2007		2008-2012		2013-2017		1990-2017	
	d	Decoupling state	*d*	Decoupling state	*d*	Decoupling state	*d*	Decoupling state
Germany	1,720	Expansive negative decoupling	-2,106	Strong decoupling	-0,057	Strong decoupling	-0,257	Strong decoupling
UK	-0,283	Strong decoupling	-6,429	Strong decoupling	-0,168	Strong decoupling	-0,564	Strong decoupling
Italy	0,908	Expansive coupling	1,239	Recessive decoupling	2,735	Expansive negative decoupling	0,313	Weak decoupling
US	-0,107	Strong decoupling	-1,254	Strong decoupling	0,418	Weak decoupling	-0,135	Strong decoupling
China	1,069	Expansive coupling	0,807	Expansive coupling	0,091	Weak decoupling	0,668	Weak decoupling
India	0,655	Weak decoupling	1,092	Expansive coupling	0,514	Weak decoupling	0,666	Weak decoupling
Russian Federation	0,212	Weak decoupling	1,021	Expansive coupling	1,009	Recessive coupling	0,150	Weak decoupling

APPENDIX F: Carbon intensity of energy

F.1 Carbon emission coefficients for the main fossil fuels

Table F.1 - Carbon emission factors of different energy sources. Source: Meng et al., 2018.

Energy (104 tons)	Coal	Coke	Crude Oil	Gasoline	Kerosene	Diesel Oil	Fuel Oil	LPG	Natural Gas
Carbon emission factor	0.7668	0.8546	0.5854	0.5561	0.5737	0.5912	0.6176	0.5034	0.4478