UNIVERSITA' DEGLI STUDI DI MODENA E REGGIO EMILIA

Department of Economics “Marco Biagi”

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TESTING THE ENVIRONMENTAL KUZNETS CURVE IN CHINA THROUGH A SPATIAL SIMULTANEOUS EQUATION PANEL MODEL

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Abstract

The main aim of this research is to statistically test the existence for the Environmental Kuznets Curve (EKC) in 30 Chinese provinces. To this extent, official data for 3 main pollutants (SO_2, $PM_{2.5}$, Waste-Water) and CO_2 have been analyzed, in the period between 1999 and 2018. The main contribution that will be provided foresees the introduction of a new econometric model, which has never been employed in the previous EKC literature in China. The model takes inspiration from the Geographically Weighted Panel Data Regression (Yu et al, 2010) and improves it through the application of instrumental variables methods (H. Baltagi 2005), which allows for a Simultaneous Equations Model analysis. The results show a great heterogeneity between provinces, which depends also on the pollutant/GHG which is observed. The EKC theory is not confirmed in the Chinese case, in fact few evidences of inverted U-shaped curve have been revealed only in the case of SO_2. In conclusion, basing on the statistical results, the strategy of "Get rich first and clean up later" seems to be naturally inefficient, as far as economic development alone is not enough to gradually reduce the environmental pressure. For this reason, public intervention in terms of specific regional strategies is supposed to be necessary, in order to face the environmental issue.

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Environmental Kuznets Curve Theory in China

The EKC theory takes origin from the "Kuznets Curve" in Development Economics, which naturally was meant to be the inverted U-shaped curve pointing out the relationship between per capita GDP and income inequalities (Gini's coefficient[1]). The theory basically supposed that the increase in per capita GDP would lead towards an increase in income inequalities, however, in the long run, the path would reverse the direction by reducing income inequalities and maintaining persistent levels of per capita GDP growth.

The same description of the phenomenon has been reported in the study of Environmentally Sustainable Development, pointing out that the increase in per capita GDP could follow the same pattern with respect to pollution. To this extent, higher levels of per capita GDP should lead towards increasing levels of environmental degradation at first, with a subsequent decrease in the level of pollution as economic development continues to grow. Several researches have been carried out in this field, reporting different results. The theory, in order to be validated, needs to be empirically and statistically tested.

As regards the reliability of the research, the length of time periods and the geographical extension of the analysis can be considered a great limit to overcome. The first limit is due to the availability of small data, which will be collected in bigger amounts in the next decades. The second is due to the possibility to extend the research to big areas, which comprehend the developed and developing countries at the same time (testing also for the existence of the Pollution Heaven theory). In fact, it is normally shared the conviction that industrialized countries have been able to follow a reduction in its polluters' emissions, without incurring in decreasing wealth, nonetheless it is not clear if they solved a problem or if, on the contrary, they just shifted its own environmental impact to developing countries.

In addition, according to Zhibao (2019), has been shown that the economic scale, industrial structure and technological level have important influences on the shape of the EKC, with the scale effect acting as a monotonic increasing cause for the environment degradation in the first phase of development. This is particularly important to take into consideration in the Chinese case, in which

[1] Gini Index: is an index (between 0 and 1) that measures the inequalities in wealth distribution. If the ratio is close to zero it means that there is no inequality in the economic distribution of wealth.

the scale effect seems to be prominent (especially regarding CO2 emissions).

The aim of this research is to define the existing relationship between 3 main pollutants (SO_2, $PM_{2.5}$, wastewater) and the CO_2 (the main Green-House Gas emission in China), with respect to the economic development (per capita GDP) in China. The question that arises is whether economic development could be naturally compliant with the environmental quality, or whether a public intervention is considered necessary in order to reduce environmental pressure.

The scientific contribution of this research regards the introduction of a new model into the EKC literature in China, namely a Three-Stages Least Squares Geographically Weighted Panel Data Regression, (3SLS-GWPR), applied to all the above described pollutants/GHGs, in the period between 1999 and 2018.

Economic growth in China (1970-2018)

In the last decades, strong economic development has shaped the current situation in China promoting in some extents the improvement of people's general living conditions and enhancing the social standards. In fact, in the period between 1970 and 2018, especially since the Chinese economic reform and opening up in 1978, despite some slight reductions due to the recent global financial crisis started in 2008, the Chinese annual average growth of GDP has been attested to more than 9% (Data: The World Bank - TWB) with a level of annual GDP equal to 9×10^7 milion Yuan in 2018 (Data: National Bureau of Statistics of China - NBS). Due to such a key transformation, which has been generally recognized as the "Chinese Miracle", significant changes in social, economic and political environments have occurred. China overtook Japan in 2010 becoming the world's second-largest economy behind the United States (Chandran and Tang, 2013).

In the same period, a demographic boom has occurred, the population grew by a 68% rate in the whole country (Data: The World Bank - TWB) making China be the first populous country in the world before India and USA, while GDP per capita rate has averagely grown by 8% , making China be the first economic developing country worldwide (Data: The World Bank - TWB).

Economic openness policies have stimulated the increase in international trade with several countries, the levels of trade in relation to GDP has increased by 6,7% from 1970 to 2018 making China be the first exporting country in the world, overtaking Germany in 2005 and obtaining the share of 15% in 2018 worldwide (Data: Observatory of Economic Complexity - OEC). Moreover, the total value of exports grew by 92% between 1999 and 2018, with an absolute value equal to 2×10^{12} USD in 2018 (Data: National Bureau of Statistics of China - NBS).

As the economy steadily grew in China, the financial sector entered a stage of huge development. At an international level, an increasing number of foreign investors started to be attracted, bringing high levels of capital. As a result, the net inflows of foreign direct investments passed from 430 million USD in 1982 to 203×10^3 billion USD. At a national level, the percentual domestic credit provided by financial sector with respect to GDP passed from 39% in 1977 to 218% in 2018 (Data: The World Bank - TWB).

Urban areas which are generally acknowledged to be more prosperous, offering better standards of life in terms of job opportunities, health facilities, infrastructure services, and increased income, started to benefit from foreign investments and commercial centrality, hence growing in dimension and attracting most of the population. As a result of such an agglomeration, urban population grew by 40% in the period between 1990 and 2015, reaching the share of 56% on the total population, while the area of built-up land has grown from 29.6 million ha in 1996 to 33.1 million ha in 2008, with a decrease of arable lands by 8.4 million ha in the same period (Y. Li et al, 2014). Urbanization had a great impact on economy given that in 2017 urban population accounted for more than 80% of China's GDP. Some improvements have occurred also on the rural areas, especially due to the policy known as the “Household Responsibility System” (HRS) in the late 1970s and early 1980s, which established the rural households’ rights to utilize jointly-owned land, and the right to dispose the marginal output thereof in the open market (Solarina, 2017).

The economic, political and social transformation has gradually affected the energy and the industrial configuration. The industrial sector in China represented the largest share of energy consumption in 2015 with more than 68% of total energy consumption (tons of Standard Coal Equivalent (SCE)[2]), followed by the residential (12%) and transportation (9%) sectors, determining also the largest share of GDP composition with a level of 34%, followed by wholesale and retail 9.5% and financial intermediation 8% in 2017. Moreover, the shares of primary, secondary and tertiary industries have changed in the period between 1999 and 2018 respectively passing from 16%, 45% and 38% to 7%, 41% and 52% in relation to the total amount of value-added, denoting an increasing weight of the tertiary sector in the economy (Data: National Bureau

[2] SCE: metric unit of a generic energy source burned in order to obtain the same amount of energy obtained by burning a metric unit of coal.

of Statistics of China - NBS).

Economic growth is closely related to energy consumption, as higher economic growth requires more energy consumption, and more efficient energy use needs a higher level of economic growth. (Liang and Yang, 2019). In this regard, the total amount of energy consumption in China grew from 146 x 10^7 tons of SCE in 1999 to 464 x 10^7 tons of SCE in 2017, accounting in 2016 for approximately 23% of the total world consumption of energy (Dong et al, 2017). The rapid growing energy demand required a huge amount of low-priced energy resources, making coal be the first choice due to its availability and relative low price. Given that the thermal efficiency[3] of coal is considerably lower than that of other energy sources, such as oil and gas, China undertook the traditional path of development "get rich first and clean up later", provoking higher emissions of CO_2 (Hao et al, 2018). In 1999 the energy consumption mix of the main energetic sources was composed by Coal 68.5%, Petroleum 22%, Hydro/Nuclear/Wind Power 7.5% and Natural Gas 2%. In 2018 the configuration changed, with Coal equal to 59% of total energy consumption, Petroleum 19%, Hydro/Nuclear/Wind Power 14% and Natural Gas 8% (Data: National Bureau of Statistics of China - NBS). As regards nuclear energy, in the period between 1993 and 2016 the consumption increased from 0.4 Mtoe 48.2 Mtoe, growing nearly 120 times over, with an average annual growth rate of 22.1%, while the consumption of natural gas in China has increased from 1.1 bcm[4] to 210.3 bcm, nearly 190 times, with an average annual growth rate of 10.8%. (Dong et al, 2018).

The trends in the energy composition show the efforts made by the Chinese Government in order to shift from a coal based industrial economy to cleaner energy sources. Such a transition is not easy to achieve, in fact even if China has abundant renewable energy resources (hydropower, solar, wind, geothermal and biomass), the technologies available in the early stages have not been widely adopted due to the high investment costs and the technical barriers.

The quality of Chinese domestic technology in the energy sector has been under development for many years and this forced energy developers to import costly generating units overseas. In the period between 2000 to 2018, energy imported quantities passed from 14 x 10^4

[3] Which means that for the same amount of heat, much more coals than oil and gas should be combusted.

[4] Bcm: stands for "billion cubic meters".

tce[5] to 100 x 10^4 tce and export passed from 9 x 10^4 tce to 13 x 10^4 tce (Data: National Bureau of Statistics of China - NBS). The historical configuration of China as an energy importer country, limited the development of the local sector. However, more recently, due also to the public policies, international manufacturers got more willing to invest in it and the sector knew a great development, generating a decrease in clean energy technologies costs. Chinese Government has stimulated investments in renewable energy and related transmission infrastructure through various economic and financial incentives. Chinese firms arranged $473 billion on clean energy investments during the period of 2011–2015 (Solarina, 2017). In the period between 1965 and 2016, renewable energy consumption has increased by nearly 70 times, from 5.0 Mtoe[6] to 349 Mtoe, and it is expected to increase by approximately 20% from 2016 to 2020, representing more than one-fourth of the total generation capacity. (Dong et al, 2018).

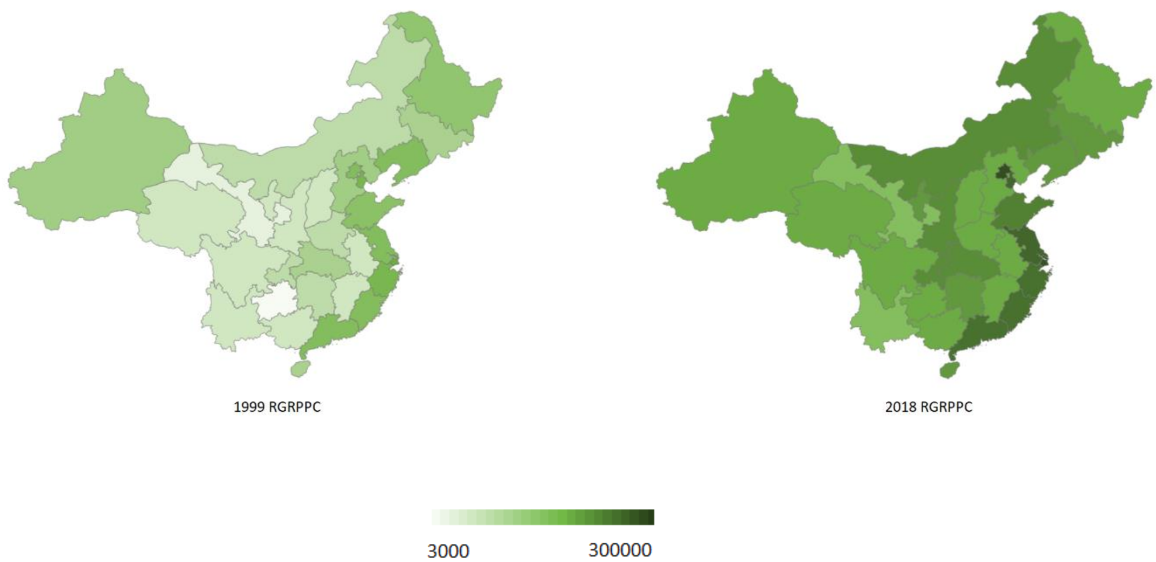


Fig.1 Shows the economic evolution in China at a provincial level.

One of the main indexes which reveal the increasing technological development is the total

[5] Tce: stands for "tonne of coal equivalent", the energy obtained by burned a tonne of coal.

[6] Mtoe: stands for "million tonnes oil equivalent", the energy released by burning one tonne of oil.

energy efficiency[7], which passed from 69.4 to 73.7 in the period between 2000 and 2017(Data: National Bureau of Statistics of China - NBS). Moreover, an important evidence of the increasing quality of the energy management system is provided by the elasticity ratio[8]. In the period between 2000 and 2017, the elasticity ratio of energy consumption passed from 0.54 to 0.42, while the elasticity ratio of electricity consumption[9] passed from 1.12 to 0.96 (Data: National Bureau of Statistics of China - NBS).

Environmental issues

The most evident benefit of the economic growth is the great alleviation of poverty[10], resulted in shared prosperity and welfare. According to The World Bank, poverty in China is mainly concentrated in rural areas while urban areas are generally rich. In the period between 2013 and 2015, the average consumption growth of the bottom 40% of the population has been 1.75% higher than the average consumption growth of the total population. Moreover, in the period between 1990 and 2015, China has been able to lift almost 800 million of people out of extreme poverty. In addition, there is evidence of falling income inequality as measured by the Gini index, which felt from 49.1 in 2008 to 46.5 in 2016.

Despite the economic results, according to the United Nations Development Programme (UNDP), China's Human Development Index (HDI)[11] has been attested at 0.752 in 2018, ranking in the 86th place in the world, suggesting the existence of barriers to human development, such as gender gaps and inequalities, social injustice and environmental concerns. China's efforts in poverty eradication have generally been recognized, however, economic growth alone is insufficient, especially when it is achieved at the expense of environmental quality, which is

[7] Efficiency of Energy Processing and Conversion refers to the ratio of the total output of energy products kinds after processing and conversion to the total input of energy for processing and conversion. It shows the current conditions of energy processing and conversion equipment, production technique and management.

[8] Ratio of Energy Consumption is an indicator to show the relationship between the growth rate of energy consumption and the growth rate of the national economy.

[9] Elasticity Ratio of Electricity consumption is an indicator to show the relationship between the growth rate of electricity consumption and the growth rate of the national economy.

[10] The extreme poverty line is internationally measured by the percentage of inhabitants living on $1.90 or less per day in 2011 purchasing price parity terms.

[11] The Human Development Index captures human development progress, taking into consideration data on people's health, education and income in one single value.

considered as one important component of sustainable development. According to Liu (2012), developing countries which base their development on the philosophy "get rich first and clean up later", could risk severe environmental damages, social injustice and income inequality. The main issue is due to a phenomenon known as environmental relegation, which supposes that impacts on different communities could differ in the same country. In this regard, poor people in polluted areas could probably become poorer and be relegated into these areas, on the contrary, the richest communities could become even richer and benefit from better environmental conditions.

After the realization of a development strategy of high investment, export orientation, and energy-intensive manufacturing at the expense of environment, in 2014 China entered a new phase of economic development, named a "new normal". In this stage the annual economic growth rate slowed down to 7%.

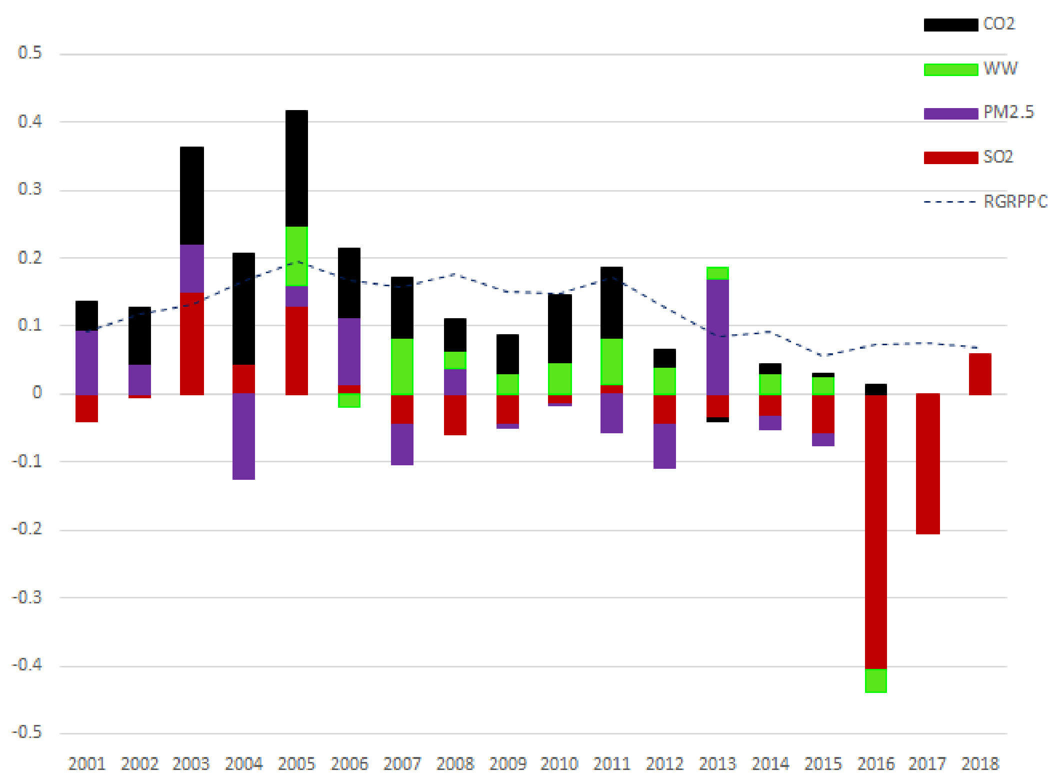


Fig.2 Shows the percentual growth of the Real Gross National Product Per Capita RGNPPC and Pollutants/GHGs (data provided by National Bureau of Statistics of China)

Even if China's rapid growth has lifted hundreds of millions out of poverty, it intensified environmental pressure. (G. Du, 2018). In the recent years, pollution events have frequently occurred, spreading a diffused environmental concern between the international communities, while air qualities of more than 70% of Chinese cities in northern and eastern regions (with denser population, higher levels of industrialization and economic development) were unable to meet the standards set by the World Health Organization.

According to the WHO, these cities suffered by severe water contamination and tremendous solid waste generation (Hao et al, 2018). China has been facing an increasingly severe crisis of water shortage for a long period. Insufficient water endowment and local overuse have become key issues in sustainable development. A series of policies have been adopted by Chinese governments in order to stop the growth of water use. These actions had a significant effect on water consumption in 2014, in fact after a long period of continues increase Chinese total water use decreased for the first time with a sustained and stable annual growth of the GDP (X. Zhao 2017). As regards solid waste generation, in 2018, the total stock of historical untreated SW has reached 6 billion tons in China, occupying 500 million square meters of cultivated land.

In that same period almost 200 out of 660 cities across the country suffered by a great concentration of Solid Wastes. The volume of China's SW is still large, and its growth rate has grown fast in time (S. Gui 2018).

One of the main causes of environmental pressure has been the rapid increasing energy consumption, which produced high quantities of CO_2 emissions. Due to massive consumption of fossil fuels, CO_2 emission volume in China has continually increased: from 20.75 billion tons in 1990 to 91.40 billion tons in 2016, according to data released by the International Energy Agency (IEA). China's CO_2 emissions rose sharply in the last years, surpassing the United States in 2006 as the largest CO_2 emitter in the world (J. Sunday, 2017). In this regard, Coal was supposed to be the cause of various pollutants, such as sulfur dioxide (SO_2), nitrogen oxides (NOx), and fine particles matters ($PM_{2.5}$) (Hao et al, 2018).

Since 1990, the electricity and heat generation sector grew the most, representing 48% of Chinese CO_2 emissions in 2009 (Cheng and Li, 2019). In the recent years, many solutions have been employed in order to reduce the consumption of coal and limit the emissions of the main pollutants. The China's National Bureau of Statistics communicated in 2018 that after four years of decrease, China's coal consumption rose for a second year in a row in, pointing out that coal's share of total energy consumption felt by 1.4%, attesting at a level equal to 59% for the first time, as cleaner energy such as gas, nuclear power and renewable energy combined accounted for 22.1

percent, up 1.3 percentage points. This event brought China closer to its target of reducing the share of coal in its energy mix to below 58% by 2020. As a top emitter, China made a commitment in the 2015 United Nations Climate Change conference in Paris to peak CO_2 emissions and reduce CO_2 emissions per unit of GDP by 60% to 65% by around 2030 compared to the 2005 level.

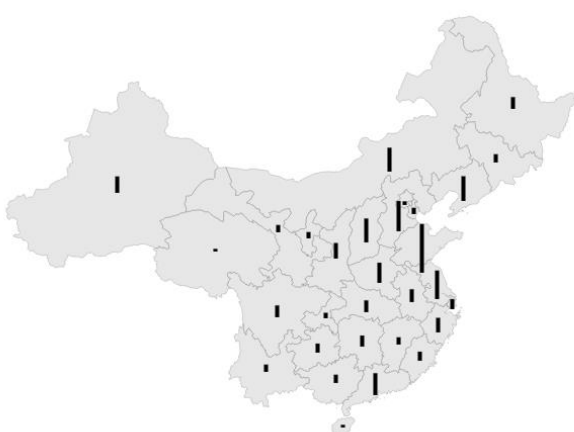
In order to achieve the target, the Industry sector in China, which contributed to about 70% of total national energy consumption, 83% of total SO_2 emission and 80% of total smoke and dust emission (National Bureau of Statistics) in 2016, and which is the major emitter of CO_2, contributing around 80.1% of the total emissions in 2013 by the estimates of the International Energy Agency (IEA), is obviously considered as the main area in which carbon mitigation policies have to be developed. In this regard, it is important to consider that industry sectors have different impacts on CO_2 emissions depending on their industrial processes.

In China, industry can be divided into specific sectors, including manufacturing, electricity, mining, and heat production. during the recent decade, energy-related CO_2 emissions from these three sectors in China kept growing and vary by their different energy mix and diversified industry characteristics. For example, it should be noted that, since 2012, the electricity and heat production sector has surpassed the manufacturing sector, becoming the top carbon emitter in industrial sector. Because of this heterogeneity, in order to design more precise polices, there is further need to investigate the evolution in the carbon emissions composition among these sectors. (Yuan Wang 2017).

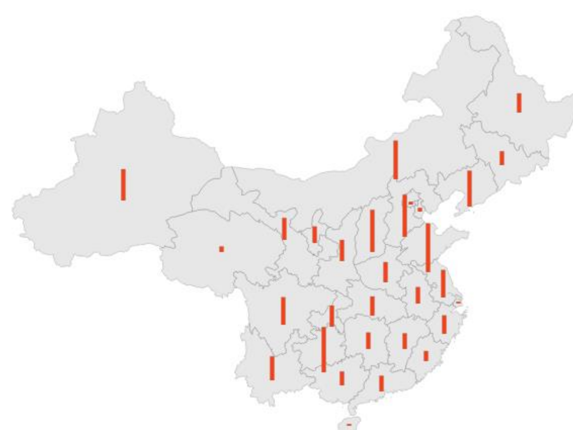
The occurrence of pollution not only is a threat for the environment and for human health (especially for the poor, which are more vulnerable), but also generates significantly negative impacts on the economic system. In fact, air pollution kills over 1.6 million people in China, and it costed the government approximately 5 billion RMB to control the air pollution in Beijing in 2013 (Zhang et al., 2017). The relationship between economic growth and pollution could so be reciprocal. According to the 2010 Global Burden of Disease Study (GBD), deaths caused by air pollution in China could led to huge economic losses, equivalent up to 7% of China's annual GDP, result which is in accordance with The World Bank, which pointed out that economic losses caused mainly by air pollution accounted for approximately 7.7% of China's GDP in 1995. (Wang, 2010).

Another important phenomenon to be considered is the relationship between financial markets and stringent environmental policies. In fact, in the short run the stock market usually reacts negatively to the announcement of a new environmental policy, although positive effects and profits are observed in the long term due to public recognition and the potentially avoided costs of liabilities and compliance (M. Guo et al, 2019). In this regard, the Chinese Government has a strong incentive to mitigate climate change and pollution. At first, pollution mitigation could be the source of new profitable markets, in which China could enter as leader and first comer; secondly with the ability to conciliate economic development and environmental safety, China could establish itself as a geopolitical superpower, gaining in prestige and trust and obtaining more soft power.

Nowadays, China and EU are the main global climate leaders, in fact despite the recent reluctance of the USA towards active climate actions and the formal withdrawal process started on the 4th of November 2019 by the Trump administration, France and China's showed a joint support for the "irreversible" Paris Agreement. This is a very important political step, in fact, China is the world's largest GHG emitter, it contributes for the 23% of world emissions, with its 19% share of the world's population and 15% share of the world's GDP. According to British Petroleum, the global Chinese carbon emissions share in 2017 was 37.2%, while EU and the US respectively accounted for 10.6% and 15.2%. (Y. Hua and F. Dong, 2019). Progress on global environmental issue objectives will be difficult to achieve without the participation of China, which role is important also because of the Pollution Heaven theory, which suggests that environmental issues should not be faced only at a national level but require organized international and global actions.



CO2 (Mt)



SO2 (ton)

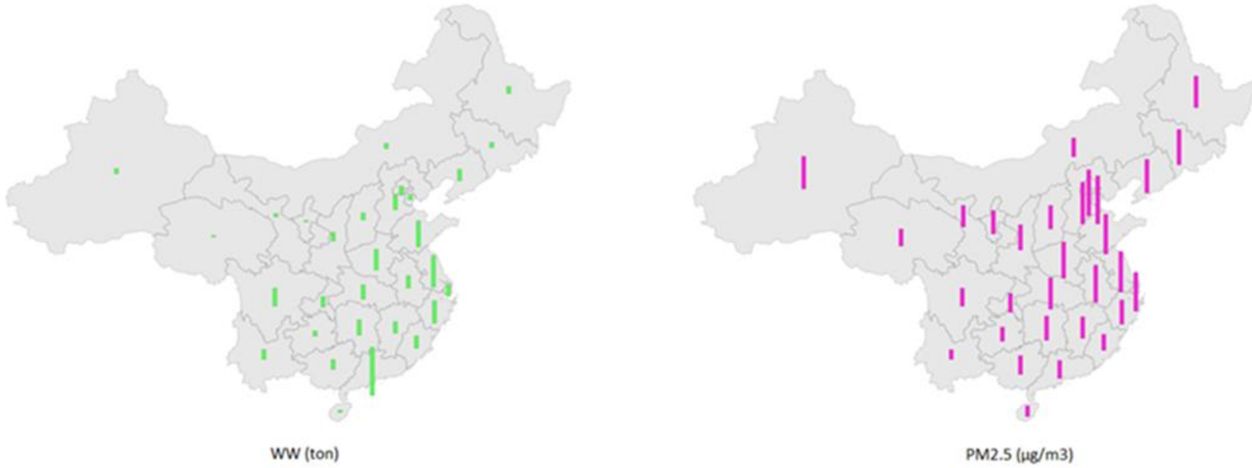


Fig.3 Shows the environmental issue in data. CO_2 (2016), SO_2 (2018), WW (2016), $PM_{2.5}$ (2015).

International Policies

In 1992 the United Nations (UN) issued the United Nations Framework Convention on Climate Change (UNFCC), legally effective in 1994, which is considered as the first international climate treaty to deal with the rising problem of climate change. The original aim of the treaty was the stabilization of GHG concentrations at a level that would prevent damaging anthropogenic interference with the climate system, without setting limits on emissions or establishing enforcement mechanisms for the single countries. Nonetheless, the framework allowed for the possibility to sign specific international treaties, also called “protocols” or “agreements”, in which stringent limits to emissions cold be defined.

In 1997 the UNFCC ratified the Kyoto Protocol, legally effective in 2005, which rules and requirements for implementation were further developed in the Marrakesh Accords in 2001. Kyoto Protocol's first commitment period started in 2008 and ended up in 2012. In this period, limitations on the main pollutants (CO_2, CH_4, N_2O, HFCs, PFCs, SF_6) were agreed for the Annex I countries (which is a list of developed countries), under the principle of "common but differentiated responsibilities." Foreseen by the article 3.1 of the United Nations (1992). The protocol states that Parties must undertake domestic policies and measures to reduce GHG by minimizing any adverse impact of on other Parties, especially developing Parties, moreover, they must provide additional financial resources to advance the implementation of commitments by developing countries.

One of the most interesting mechanisms introduced was the trading system of emission credits. Under this mechanism, Annex I Parties could trade emission credits by each other, without affecting the total amount of emission quotas collectively assigned. The acquisition for a single Party was unlimited, while the possibility to sell was limited by the Party's commitment period reserve (CPR) (UNFCC, 2008). As regards China, the country was not included in the Annex I list, so to that point, no binding restrictions were foreseen. However, China could benefit from the resources that developed countries should provide in order to advance the implementation of their commitments (once again is highlighted the importance of figuring out the existence for the Pollution Heaven theory).

In 2009, the 15th Conference of the Parties (COP15) of the UNFCCC was held at Copenhagen. The main objective was to renovate climate agreements that were supposed to come to an end in 2012 when the Kyoto Protocol would have expired. The focus was on the need to establish specific limits to CO_2 emissions, but the strong limitations proposed by EU were considered too risky by the rest of the countries. The result was the definition of non-binding objectives on carbon emissions, while parties decided to postpone the negotiation about legally binding commitment and extension of the Kyoto Protocol to later conferences in Cancun, México, in Durban, South Africa, and in Qatar. (Y. Hu and C. Rodríguez Monroy, 2012). In this occasion, the Chinese government announced that by 2020 its CO_2 emissions per unit of GDP would be 40–45% lower than that in 2005 (D. Fang, 2019). The same commitment was formally undertaken by US and EU with respective values of 17% and 20-30%. The agreement has been strongly criticized, due to concerns about the success of international climate agreements. Scientists and the public opinion were confident about a concrete decision in order to limit the rising climate change, by defining clear and binding objectives. However, the commitments were only formal, and contrasts were rising between Parties concurrently to the end of the Kyoto Protocol.

In such a climate of pressure was held in Cancun the16th session of the Conference of the Parties (COP 16) to the United Nations Framework Convention on Climate Change (UNFCCC). Firstly, the Green Climate Fund has been established, a new fund in which countries pledged up to $100 billion per year in new financing for climate-related aid towards developing countries; secondly, the goal of keeping global temperature under 2°C was introduced, considering a more stringent goal of 1.5°C based on newer scientific information; finally, a formal process for reporting mitigation commitments into the formal UNFCCC system has been defined. (Brookings, 2016). Once again, the new agreements didn't perfectly match the expectations, no binding decision were undertaken yet, but signals of improvement were showed. In fact, some approaches at that point defined the full legitimacy of the processes and therefore may be a useful step towards a future overall agreement. Since this conference, the debate insisted on the need to provide finance, technology and capacity-building support to developing countries to meet urgent needs to adapt to climate change and to speed up their plans to adopt sustainable paths to low emission economies.

In 2011 the 17th Conference of the Parties (COP17) was held in Durban and was characterized by a big debate between developed and developing countries. One of the main contentions since then, was whether the emerging developing countries, like China, should make commitments and legally bind themselves to (GHG) reduction target in near future. From one side, some developed countries refused to renovate their commitment in the second period of the Kyoto protocol unless the main developing countries would have been involved in the agreements. From the other, these countries claimed that their biggest concern was still to eradicate poverty and that developed countries should be responsible for the largest share of historical and current global GHG emissions. As a result, China proposed five conditions for joining the treaty legally effective since 2020: firstly, the protocol must be legally binding; secondly, Green Climate Fund, which was still at a paperwork stage, must be concretely established; thirdly, the mechanism agreed in the former conferences in the areas of technology transfer, reforestation, transparency, and capability building should be established; fourthly, evaluation of developed countries fulfilling their commitments during the protocol must be provided; finally, China would be responsible of the environmental issues basing on its level of development, as foreseen by the article 3.1 of the UN. (Y. Hu and C. Rodríguez Monroy, 2012). The outcome of the conference was not very satisfactory for the scientific community and environmental groups, which warned that the deal was not sufficient to avoid global warming beyond 2 °C, as more urgent action were needed. The real importance of Durban conference was that governments reintroduced the topic of legally binding global agreements involving the world's major emitters, something that was not obvious especially after Copenaghen's outcomes.

In 2013 The United Nations Climate Change Conference, COP19 was held in Warsaw. In this date, the main objective was to encourage Parties to submit their "intended nationally determined contributions" (INDCs) to the Paris Agreement well in advance of COP 21. These documents should represent each country's self-defined mitigation goals for the treaty which would be legally effective since 2020. As a result, 192 countries accounting for almost 97% of global emissions submitted INDCs to the UNFCCC secretariat. Developed countries generally opted for absolute emissions reductions, while developing countries offered a range of approaches, such as absolute economy-wide targets, reductions in emissions intensity (emissions per unit of GDP), reductions from projected "business-as-usual" emissions, and reductions in per-capita emissions. (Center for Climate and Energy Solutions). The conference was considered as an important staging point on the road to the Paris Agreement, in fact there wasn't yet a document for the agreement or a consensus on the legal form (The Guardian, 2013).

In 2016 The Paris Agreement opened for signature on the 22nd of April (the Earth Day), at UN Headquarters in New York. The agreement couldn't take effect until at least 55 nations, representing at least the 55% of global emissions, formally would have joined it. This requisite was satisfied on the 4th of November. Since then, more countries ratified and continue to ratify the Agreement, reaching a total of 197 Parties in early 2019. (UNFCC). The Paris Agreement reaffirmed the 2°C goal and finally established a set of binding procedural commitments. Parties committed to prepare, communicate and maintain their NDCs; to pursue domestic mitigation measures in order to achieve their goals; and to regularly report on their emissions and progresses. Finally, the treaty mobilized $100 billion a year for the Green Climate Fund, devoted to developing countries by the beginning of 2020. The agreement also encouraged other countries to contribute voluntarily and China offered 3 billion US$ in 2015 to help other developing countries. (Center for Climate and Energy Solutions). As regards the commitments, China submitted in Paris its Intended Nationally Determined Contributions (INDC), a commitment in which the largest consumer of coal and first CO_2 emitter in the world pledged to reach its CO_2 emission peak before 2030 and to reduce its CO_2 intensity[12] by 60-65% with respect to 2005 (L. Jiunxian, 2019). At that point, the real concern was focused on single differences of the Parties, because of this, the carbon emission price and its trading system alone couldn't solve the climate change issue, which should need a multiple dimensions solution. In this regard, some complementary policies are supposed to be necessary, such as fiscal and labor market reforms. In terms of climate policy architecture, alignment between global and domestic policies could help the single countries, by integrating GHG reduction emissions in development programs. Countries could then adopt some Nationally

[12] CO_2 intensity: CO_2 emissions per unit of GDP.

Appropriate Mitigation Actions (NAMAs). NAMAs are supposed to be actions that Parties can voluntarily implement, domestically funded (unilateral NAMAs) or internationally funded (supported NAMAs). These mitigation actions are not supposed to be specifically finalized to carbon abatement, they could be devoted to preventing energy poverty traps, improve energy efficiency or finance international cooperation (J. Li et al, 2017).

National Policies

When treating national policies in China, it becomes very important to introduce the Five-Year plan. In fact, Five-Year plans are fundamental tools in the Chinese political system, which have turned to be almost the unique driver of economic and social development. This governance tool played a central role in energy saving and emission reduction. Three main features can be pointed out: firstly, it promotes management according to long term objectives in span of 5 years, secondly, the assessments of provincial level policies are used as critical evidence to evaluate results over objectives and to strengthen the responsibilities; thirdly, the managerial role of the government is as decisive as the balancing role of the market. Five-Year plans could play a vital role in energy saving and emissions reduction in China.

During the 9th Five-Year Plan (1996-2000), the economic growth rate was averagely above the 8.6%, and the energy consumption growth rate was 1.1%.

In the 10th Year-Plan period (2001-2005) however, the situation changed: the economic growth rate was 10.2%, the energy consumption growth rate was 9.4% and the CO_2 emissions growth rate was 18%, a condition that generated strong environmental pressure. (H. An-Gang, 2017). Nonetheless, until that point, energy efficiency policies and renewable energy policies were almost non-existent, and the public debate used to make little mention of them (L. Hong et al, 2013).

During the 11th Five-Year plan (2006-2010) the situation was very different. The environmental condition in China became more complicated as the economic growth rate rose up to 11.2%, demanding more energy consumption. At that point, the public opinion got more aware regarding the environmental issue. The international communities already ratified the Kyoto Protocol in order to face the global rising of climate change. Even if there were not limitation foreseen by international treaties, in this period, the Government started to face some internal environmental degradation problems. The 11th Five-Year Plan set up some targets: the percentage of its share in the economy of service sector increase by 40.5%, achieving a level of 43.0%; the employment rate in the service sector by 31.3%, and 34.8% was achieved; the energy consumed per GDP by 20.0%, and 19.1% was achieved (H. An-Gang, 2017). Regarding the issue of legally binding GHG emission reduction obligations, the Chinese government put forward a target in the 11th Five-Year to reduce chemical oxygen demand (COD) discharge. by the end of 2014, COD discharge decreased by 8% from its 2011 level (Zhang et al 2017). Forceful initiatives relating to air pollution control began at a national level with the 11th FYP, which for the first time set several mandatory quantitative targets for environment and energy. In this regard, the energy intensity was planned to be reduced by 20% and total sulfur dioxide (SO_2) emission by 10% by 2010 from their respective 2005 levels (Y. Feng et al, 2019). As far as regards CO_2 intensity, China achieved a reduction of 21% during the 11th FYP (J. S. Riti, 2017). At the end of the period, China declared the achievement of its energy intensity reduction target for the 11 FYP, adopting a positive attitude and various actions to face environmental issues, and stating that all these actions and targets were directly approved and legalized by its National People's Congress. Chinese Government employed the command and control policies, which caused the shutdown of power plants and heavy industries with significant incremental social costs for the economy and raised concerns about unemployment and political stability. (J. Li and X. Wang, 2012).

Moreover, in 2007 several economic instruments such as restrictive policies on export of resources and energy intensive products, have been introduced in order to encourage the investments in green technologies and to incentive the consumption of low carbon goods and services. The main objective was to increase the cost of dirty technologies, provoking a substitution effect (J. Li and X. Wang, 2012). In the FYP several important energy saving projects, aimed at optimizing the industry structure and adjusting the economy structure, have been pointed out, in order to shift the driving force of economic growth from industrialization to the service sector. As regards the renewable energy policies, China announced the development plan for Energy and renewable energy in 2008. The installation capacity of hydropower, biomass, wind power, solar hot-water system and solar PV was expected to respectively reach the levels of 190 million KW, 5.5 million KW, 10 million KW, 150 million KW and 300 million KW, targets that have been achieved in 2009. In addition, a plan for nuclear power development was announced in 2007, setting the target to create an installation which capacity was planned to reach the level of 40 million KW by 2020. (X. Yuan and J. Zuo, 2011).

During the 12th Year plan (2011-2015), the international debate was fierce, and China was asked by the developed countries to contribute to GHG global emissions reduction. At that point, active involvement in the emissions reduction program became unavoidable. The national macroeconomic situation was very different with respect to the past, in fact the economic growth passed from high rate to moderate-high rate. China decided to put more efforts in the economy conversion already started during the 11th FYP, which mainly consisted in a radical structure transformation, with the share of the service sector being increased at the expense of the dirty industry. In this regard, progress in energy saving and emissions reduction has been pursued through the phase out of outdated production methods and the reduction of energy intensive industries, such as the steel industry, the building material industry, the non-metal mining industry, the chemical industry, and the petrochemical industry. To this extent, China provided facilitated access to financial credits and capital for high efficiency firms. (J. Li and X. Wang, 2012). In the period between 2010 and 2013, the share of the secondary sector dropped from 56.8% to 48.3%, with an increase in services from 39.3% to 46.8%. Moreover, the coefficient of elasticity of energy declined slightly from 0.58 to 0.48 (H. An-Gang, 2017). In order to stimulate green growth, 7 new industries have been developed, such as: advanced materials, renewable and alternative energy, information technology, innovative equipment manufacturing, biotechnology, energy conservation and environmental protection and new energy vehicles (J. Li and X. Wang, 2012). As a consequence, the proportion of new energy and renewable energy constantly increased in China. (X. Yuan and J. Zuo, 2011).

As regards Government intervention in energy structure, the 12 FYP proposed four essential energy saving projects, namely: energy saving reconstruction, beneficial products that save energy, demonstration of the industrialization of energy saving techniques, and further implementation of energy management contracts.

The growth of oil and gas consumption dropped noticeably during the 12th FYP, and the exploration and development of new sites faced new evolutions. The global oil price collapsed and fluctuated at a low level, which inhibited the enthusiasm for oil and gas exploration and development. (P. Jiping, 2016). Moreover, in the same period seven important projects have been proposed for recycling economy. Regarding the fundamental environmental issues, some essential projects have been proposed, including: wastewater treatment, desulfurization and denitrification, heavy metal pollution prevention and control and water environment improvement. A critical situation started to affect water resources, in fact in 2014 groundwater supply has been categorized as "bad to very bad" in more than 60% of Chinese cities, while more than 25% of China's major rivers were considered to be "unfit for human contact".

In terms of GHG reduction and pollution mitigation, very strong improvements have been achieved. In 2015 China's CO_2 emissions, decreased by about 0.7%, compared to the previous year. This result has been achieved mainly due to a 1.5% decline in coal consumption, which affected oil consumption and natural gas, respectively raised to 6.3% and to 4.7%. In 2015, coal share in energy mix accounted for less than 70%, which is to say 10% less than the same relative value in 2011. An important performance to be noticed is the reduction of electricity output decreased continuously up to 8.9% (H. An-Gang, 2017). All these interventions provoked the fall of CO_2 emissions to 1.82% in 2012-2014.

During the 13th Year Plan (2016-2020) China took a great step forwards to the green development. After the Paris Agreement, China aligned with the international pledge its national policies, issuing in the period between 2016 and 2020 the "13th Five-Year plan for Economic and Social Development of the People's Republic of China "and "Notification of State Council on 13th Five-Year plan for energy savings and emissions reduction". Moreover, the national policies have been described in a set of documents, which includes: "Opinions on Promoting the Clean Development and Efficient Use of Coal", "Upgrade and Retrofit Plan for Coal-fired Power Plants Aiming at Energy Savings and Emissions Reduction for 2014–2020", "Implementation Work Plan of Retrofits for Ultra-Low Emissions and Energy Savings of Coal-fired Power Plants" and "13th Five-Year Plan for electric power development " (M. Li and D. Patiño-Echeverri, 2017).

For the first time, the plan introduced the objective of improving the overall ecological environment quality, integrated as a core principle, and the preservation of a medium-high economic growth. In fact, a GDP growth rate between 6.5-7.0% combined with the energy consumption elasticity growth, would have been a good trade-off for China, in a period in which the service sector was expected to continue its increasing path at the expenses of the traditional industry, pushed also by the rapid digital innovation (H. An-Gang, 2017). In 2018, the Environmental Protection Tax Law of the People's Republic of China has been implemented nationwide. This intervention, stipulated that producers that directly discharge air pollutants, water pollutants and solid wastes should pay an environmental protection tax (Q. Xie, 2019). Other important policies undertaken by the Central Government were related to the introduction of energy efficiency programs and initiatives aimed at encouraging the development and deployment of low car technologies, and to the pilot Emission Trading System (ETS) projects, with the main aim of putting in place a national carbon market by 2017 (J. Li et al, 2017).

Finally, as regards the industry, the “Top-10,000 Energy-Consuming Enterprises Programme”, started during the 12th FYP, had a follow-up during the 13th FYP and new energy program was introduced, in line with the “the Energy Development Strategy Action Plan 2014-2020”, and “Made in China 2025” industrial innovation strategy. In order to achieve the new commitments, three strategies in renewable power installed capacity have been defined, as outlined in the document “13th Five-Year Plan for electric power development”. To this extent hydropower, wind and solar energy were expected to respectively achieve 340 GW, 210 GW and 110 GW in terms of power installed capacity. Another important document “Upgrade and Retrofit Plan for Coal-fired Power Plants Aiming at Energy Savings and Emissions Reduction for 2014–2020” outlined the standards for new Coal-fired power Plants (CFPPs).

EKC Literature review in China

Regarding the local situation in China, many researches have been carried out in the last decades. The advantage of a single-country analysis is due to the elimination of the issues based on the comparison between units, which is of great importance in cross-countries studies (Carson et al., 1997), and to the possibility to observe more specific phenomena on a single country level (de Bruyn and Heitz, 1999). The literature has been analyzed in detail, as a result, two main schools of thought can be defined. While the first basically supports the EKC theory, stating that the economic development allows for natural positive effects on the environment, the second does not.

Literature review in support of the EKC Theory

Up to now, most of the literature is in favor of the EKC Theory. As regards carbon dioxide (CO_2), in 2000 Auffhammer et al. published the first national discussion paper, analyzing a set of Chinese regions over the period 1985–1995, by employing a single equation model[13], and starting a large scientific tradition that would have continued in the following years. The results demonstrated the existence of an inverted U-shaped curve for CO_2 emissions, with differences across provinces. In 2004, once again Auffhammer et al. introduced an Auto-Regressive model[14], in which CO_2 estimated emissions and the economic development have been jointly analyzed by using a province-level panel data set for 30 Chinese provinces during the period 1985-2000. The result of the observation pointed out a typical inverted U-shaped curve, which confirmed the EKC hypothesis. In addition to the introduction of the new model, the scientific contribution passed through the identification of the technological effect.

In 2009 Jalil and Mahmud published a research on a country level over the period of 1971-2005 in order to test EKC hypothesis for CO_2 emissions. The analysis has been conducted through the implementation of an autoregressive model and the results demonstrated an inverted U-shaped

[13] A single equation model is basically a model in which the entire phenomenon under observation is studied by using only one single equation. Normally single equation models do not take into consideration the reciprocity effect in the relationship between two variables, analyzing only the effect that independent variables generate to the dependent variable. In order to solve this problem, simultaneous equation models (SEM) could be adopted.

[14] An Auto-Regressive model (AR) is a single equation model in which lagged terms of the dependent variable are introduced as independent variables. The reason for such a model is that the current values of the dependent variable are directly related to the past values of the variable itself. It is quite useful to integrate AR models when the phenomenon under observation is changing in time.

curve between the variables. Basing on the results it seemed that the 11^{th} Five Years Plan started to bear fruit, even if more careful considerations should be done at a provincial or regional level.

In 2012 some more contributions have been given: Xu et al. revealed the existence of an EKC between CO_2 emissions and economic development in the period between 1980-2008, while Gao et al. demonstrated the existence of an inverted-U shaped curve for CO_2 emissions in the period between 1995-2009.

In 2016 Y. Q. Kang examined the CO_2 EKC hypothesis by employing a spatial panel data model of 30 Chinese provinces in the period between 1997–2012. In this regard, a comparative analysis of the turning points between a spatial and a non-spatial panel model has been conducted. The results showed the existence of an inverted N-shaped curve between CO_2 emissions and economic growth, where urbanization and coal combustion revealed to be the main factors on increasing CO_2 emissions, and trade openness was supposed to slightly contribute to decreasing CO_2 emissions.

One more research has been conducted by Y. Wang et al. in 2017. In this research, the EKC hypothesis has been examined by taking into consideration the impacts of economic growth and urbanization on various industrial carbon emissions in three economic sectors. The research was based on a panel data set at a province-level in the period between 2000 and 2013 in China. In this regard, simultaneous estimation of the relationship between income/urbanization and disaggregated industrial carbon dioxide emissions has been carried out, by employing a panel data set together with semi-parametric panel fixed effects regression. The results showed evidences in support of an inverted U-shaped curve relationship between the economic growth and CO_2 emissions in the electricity and heat production sectors.

F. Wang et al. published another research in 2018. The EKC has been tested in a panel data set of 30 Chinese provinces in the period between 1995 and 2015, studying the effects of CO_2 over economic development. The results showed the existence an inverted U-shaped curve at a national level, moreover, an empirical analysis of the EKC has been carried out at a province-level as well. It has been demonstrated that the EKC of economic growth is present in 18 provinces, where 9 of them presented their respective turning points of per capita GDP in 2015.

In the same year K. Dong et al. published a research in which the roles of nuclear energy and renewable energy have been investigated in the mitigation of CO_2 emissions in the period between 1993 and 2016. For this purpose, the ARDL (Auto Regressive Distributed Lag) model has been employed in order to check the validity of the long- and short-run estimates. The results showed evidence supporting the EKC hypothesis for CO_2 emissions, indicating that, in both the long run and the short run, fossil fuels consumption contributes to CO_2 emissions, while environmental quality normally improves as nuclear energy and renewable energy consumption increase.

L. Junxian et al. published a research in 2018 in order to investigate whether China's development aligned with the Environmental Kuznets Curve and Pollution Haven hypothesis. A panel data set of 29 Chinese provinces in the period between 1996 and 2015 has been employed. To this extent, a fixed effects panel data model, which integrated economic growth and foreign direct investment into the same framework in order to investigate their impact on carbon emissions, has been implemented. The results revealed the existence of an inverted U-shaped curve between economic growth and carbon dioxide emissions, and an inverted N-shaped relationship between foreign direct investment and carbon dioxide emissions. Moreover, the analysis showed that energy consumption has an accelerating effect on CO_2 emissions. Decreasing levels of CO_2 could be reached through the contribution of improvements in industrial infrastructures, technology diffusion, and trade liberalization.

Another contribution has been provided by J. Li et al in 2019. In this research a panel data of 30 Chinese provinces has been employed in order to study the relationship between the carbon intensity of human wellbeing (CIWB) and the environmental sustainability, in the period between 1995 and 2016. In this regard, a spatial model has been introduced and the results showed the existence of an inverted N-shaped curve between CIWB and economic growth.

Always in 2019 Y. He et al. employed a Panel Smooth Transition Auto-Regression (PSTR) model, based on a panel data set of 30 Chinese provinces in the period between 2003 and 2017, in order to study the effects of income levels on environmental pollution and identify the EKC threshold of energy intensity. The results revealed a stepwise decreasing pattern from the western region to the eastern region for both pollution emissions and energy intensities. Moreover, the impact of income levels on pollution emissions was supposed to be non-linear and an inverted U-shaped Environmental Kuznets curve has been accepted for energy intensity.

Z. Zhou et al. published a paper in 2019 investigating the role of the underground economy on CO_2 emissions through a panel data set of 30 Chinese provinces, in the period between 1998 and 2016. The main contribution probably has been the introduction of the underground economy in the model, which has generally been ignored in the previous literature. The results concluded that an inverse N-shaped curve pattern supposed to hold for the income-CO_2 relationship in China, with beneficial contributions provided structural and technological effects on the environment.

Finally, Y. Wang et al. published one more research in 2019, showing the relationship between economic development and CO_2.

Regarding Wastewater, in 2002 De Groot et al. analyzed the impact on the environment of economic growth (GDP) and economic development (GDPPC)[15], over 30 Chinese regions during the period 1982–1997. The results pointed out a positive effect (negative relationship) of economic growth and economic development on waste water, a typical Kuznets pattern of economic development on waste gas.

In 2008, a new scientific contribution has been given by Jiang et al., by using a 31 provinces panel data analysis from 1985 to 2005 to empirically test the EKC hypothesis. The results demonstrated the existence of an inverted U-shaped relationship between per capita income and per capita waste water.

In 2015 also Kim et al. showed the existence of EKC between economic development and wastewater. In the same year, X. Zhao et al. analyzed the relationship between water use and economic growth, by employing a province-level panel data set on population, affluence, technology, urbanization, and industrial structure, over 31 provinces in China in the period between 2003 and 2014. The results showed evidence on the existence of an inverted U-shaped relationship between water consumption and economic growth, which could reach the turning point around 2021. Moreover, all five factors studied showed to have positive effects on water use at both national and regional levels. To this extent, the population was supposed to be the most influential factor on the national scale as well as in the eastern region, and technology played the most important role in the central and the western regions.

In 2018 Z. Fang et al. examined the impact of economic growth and trade openness on the environment in 261 Chinese cities over the period of 2004–2013, by taking into consideration the phenomenon of endogeneity. The research has been focused on industrial wastewater discharges

[15] In economics is very important to distinguish between economic growth and economic development indexes: the first is about the value of products and services generated by a country's economy within its borders, normally defined as Gross Domestic Product (GDP), which is also an important index of wealth; the second is the value of products and services pro-capita generated by a country's economy (GDPPC), which is an important index of development. Gross Regional Product (GRP) instead, is the GDP at a regional level, which is more suitable to execute regional analysis.

and SO_2 and showed evidence in support of the EKC hypothesis for the whole nation and for different specific regions.

As regards sulfur dioxide (SO2), Shen and Hashimoto in 2004 and Roumasset et al. in 2007 showed the first evidences for the existence of the EKC. In 2006 Shaw et al. examined the EKC from 1992 to 2001 for 99 Chinese cities. In order to better explain the shape of the curve, several new variables have been introduced such as total population at the end of the year, secondary industry share on GDP, FDI per capita based on employed people, employed people over total population, per capita governmental expenditures and senior higher educated people over total population ratio. The results pointed out the existence of an inverted U-shaped relationship between economic development and SO_2. In 2010 Shaw et al. repeated the analysis. The observation involved a panel dataset comprising air quality, income and environmental policy, for 99 cities in the period over 1992-2004. The result showed the existence of an EKC hypothesis for SO_2 emissions, which means that economic performance could be able to naturally reduce environment pressure.

One more interesting research has been provided by K. Jayanthakumaran et al. in 2011. The paper investigated the relationship between trade, growth and emissions using provincial-level data in China for water (COD) and air (SO_2) in the period between 1990–2007. The analysis basically followed three steps: at first, the income turning point of the Environmental Kuznets Curve has been estimated using quadratic log function; secondly, adopting a simultaneous equations system, the relationships between trade, growth and emissions have been estimated, confirming the dominance of scale effects over technique effects; finally, the estimated per capita turning point for EKC has been used to split data into two groups (below and above turning point income) and simultaneous equations have been separately estimated for them. The results demonstrated a negative relationship between income and emissions due to increasing levels of international trade.

In 2011, J. He et al. estimated EKC models basing on a panel dataset of 74 Chinese cities during the period of 1991–2001, including in the analysis three main air pollutants: Total Suspending Particle (TSP), Sulfur Dioxide (SO_2) and Nitrogen Oxide (NO_x). The results highlighted the impacts of economic structure, development policies and environmental regulations on the EKC shape and turning points definition. The main insight was that increasing levels of income growth were supposed to be compatible with environmental quality, even if adjustments on economic structure, development policies and environmental regulations could be necessary in order to reduce pollution.

2012 Gao et al. showed evidences in support of EKC also for SO_2, with a turning point which appears before with respect to CO_2.

Another important contribution has been given in 2015 by Kim et al. with the introduction of a new model, widely diffused in the spatial econometric analysis. In this regard, the EKC has been reconsidered by using the Geographical Weighted Regression model (GWR)[16], which main characteristic is to take into consideration heterogeneity between geographical regions. The importance of such a model lies in the fact that multiple regression coefficients are found at a province-level, resulting in a more specific and deep observation of the phenomenon. As a consequence, the global model could be compared with each single province result, allowing the understanding of the differences based on specific geographical areas. In the research, the GWR model has been applied to SO_2 emissions, water discharge, and solid waste production in 29 provinces of China during 1994-2010. The results demonstrated the existence of an EKC relationship between pollutants and economic development in many provinces, highlighting differences between pollutants in geographical areas. Nonetheless, the model adopted resulted to be quite limited, as far as it missed the evaluation of some important variables such as industrial structure, capital intensity, environmental management capacities, trade intensity, and many others. Moreover, the GWR model itself could be object of criticism, for example: at first, the lack of temporal dimension (which is typical of cross-sectional models and which enclose GWR between them) does not allow for long-term time effects; secondly, the repetition of data, which are used several times in different geographical designed areas, could lead to inflation of regional coefficients. Despite these criticisms, the model is still able to outperform the global OLS models.

More researches have been carried out regarding other pollutants. In 2004 Shen and Hashimoto gave a scientific contribution by publishing a research based on the cross-province panel data analysis, in which national data over 31 Chinese provinces have been employed, by introducing the industrial sector share, in order to take into consideration the composition effect. The results showed an existing inverted U-shaped relationship between GDPPC and 5 main

[16] The Geographical Weighted Regression model (GWR) is a typical cross-sectional model (the time dimension is not included) which allows for analysis at a regional level. It foresees that closer regions affect the results of a single region under observation, for this reason, it is important to take into consideration a wider area of analysis, in which closer neighbors' influence is stronger than farther ones.

pollutants (Arsenic, Chemical Oxygen Demand (COD), Cadmium, Mercury, and SO_2).

In 2006 Shen J. employed a SEM model by using 31 China's provincial data from 1993 to 2002 to examine the existence for the EKC relationship between per capita income and per capita pollutants. The results revealed the existence of an EKC relationship with regard to COD, Arsenic and Cadmium emissions. Another research has been published by Xu and Song. Their findings demonstrated the existence of an inverted U-shaped curve for east and central regions.

In 2015 by Kim et al provided evidences for the existing of the EKC for solid wastes. Evidences for total suspended particles (TSP) have been provided by Shaw et al., examining EKC from 1992 to 2001 for 99 Chinese cities, by J. He et al. in 2011 and by Roumasset et al. in 2007, who published a study in which environmental issue has been analyzed for several natural resources distinguishing between natural capital (water, forests, soils, minerals, fisheries and energy) and air (TSP and NO_x emissions). This last research showed a possibility for sustainable economic growth in China for both the air and the natural capital. NRKC (Natural Resources Kuznets Curve) has been analyzed by using a different approach, indeed while air pollutants analysis has been developed on the bases of the traditional EKC, NRKC's one has been carried out through the observation of the resources' extraction and the value of the extractions. To this extent, three different stages could be distinguished: in the first phase, both the extraction and the price rise at increasing rates as the economy industrializes; secondly, the extraction costs start to reduce extraction rents even in case of increasing demand, leading towards a reduction in extraction; finally because of a comparative advantage, the economy naturally starts to focus on other productive activities by importing the needed quantities and further reducing extraction. For this reason, the extraction of natural resources normally reaches a peak and then decreases, allowing a sustainable growth. As regards renewable resources, the turning point is supposed to be normally reached after a longer period with respect to non-renewable ones. The results revealed important insights. First, an inverted U-shaped EKC held both for the country as a whole and for each of the three specific designed regions, as regards per capita waste gas emissions from fuel burning and for waste water. Secondly, gas emissions from fuel burning turning point occurred at higher income levels with respect to waste water, moreover other differences were found between regions, indeed turning point in the case of central and western regions appeared at lower income levels with respect to the coastal region. This phenomenon could be explained by the fact that less developed regions, during the economic transaction, had the opportunity to adopt earlier (with respect to the developed counterpart) the most efficient technologies and regulation policies, even if delocalization of pollutant plants played as an opposite effect, due to the tendency of relocating them in developing regions, mainly in the western-China.

As regards farmland conversion, in 2014 Li et al. analyzed a panel data of 30 Chinese provinces demonstrating the existence for an inverted U-shape relationship between the factors of farmland conversion for non-agricultural use purposes and economic growth, in the period between 2000 and 2009. The results revealed that China already reached a turning point in 2008 with per capita GDP levels exceeding 3000 US dollars. To this extent, rural-urban migration didn't show significant effects with respect to this relationship, while the industrial upgrading from secondary to tertiary industries was found to help reduce farmland conversion.

Regarding other pollutants, in 2014 Luo et al. published a research in a period from 2003 to 2012 analyzing 31 provinces data for PM_{10}, NO_2 and the air pollution index (API). Three main industries have been considered and an inverted-U shaped curve has been verified for NO_2, however the results for PM_{10} suggested a negative relationship. As far as regarded API, the index showed the feasibility of a sustainable development.

in 2016 Hao et al. tested a panel data of 29 Chinese provinces during 1995-2012 to observe the relationship between GDPPC and per capita coal consumption in China. The main scientific contribution lies in the introduction of a new spatial econometric model, the Spatial Durbin Model (SDM)[17]. The results demonstrated the existence of the spatial correlations in coal consumption across provinces, and a strong evidence for the "inverted-U" shaped EKC relationship between per capita coal consumption and the GDPPC.

Another research in 2016 has been carried out by T. Li, who employed a dynamic panel data model in order to estimate a multi-variate EKC at a province-level in the period between 1996 and 2012, by including energy consumption, trade and urbanization as control variables with respect to air, water and solid pollutants. The models introduced were the GMM (Generalized Method of Moments) and the ARDL. The results revealed the existence of an inverted U-shaped relationship between environmental quality and economic development. More in detail, energy consumption showed a positive effect on various pollutants, while trade and urbanization didn't reveal a well-defined behavior.

[17] A Spatial Durbin Model (SDM) is basically a model in which average-neighbor values of the independent variables are added to the specification, in this way observations from a single region are affected by neighbors.

In 2017 Stravropolous et al. gave an important contribution to the scientific research by introducing a spatial panel data model between 30 Chinese provinces during 2001-2010. Such a model has been introduced in order to reflect the spatial association between neighboring provinces. In order to carry out the analysis, three different functions have been modelled using either the Spatial Auto-Regression model (SAR), the Spatial Error Model (SEM)[18] or the Spatial Durbin Model (SDM). The authors employed a series of test procedures aimed to find out which one of them could better explain data, and according to their results, SDM revealed to be the best option. As far as regards variables employed in the analysis, two indexes have been created, namely: the Industrial Competitiveness (as a function of labor, capital, innovation, and ability) as explanatory variable, and the Environmental Regulation (as a function of control instruments and market-based instruments) as a dependent variable. According to the obtained results, EKC theory was confirmed.

In the same year, Zhang et al. employed two unbalanced panel data sets of 27 Chinese provinces, respectively covering the period between 1990-2014, and 2001-2014. The research introduced a semi-parametric fixed effects estimation and a parametric fixed effects estimation in order to investigate EKC relationship for both COD (Chemical Oxygen Demand) and NH_3 discharge. The results showed evidence in support of an inverted U-shaped EKC.

Another research has been carried out in 2018 by Y. Hao et al. the research employed a panel data of 30 provinces in the period between 2006 and 2015. The results pointed out the evidence for an inverted N-shaped relationship between the Environmental Quality Index (EQI) and income per capita, suggesting that the overall environmental quality in China would first worsen and then gradually improve as the economy develops.

Finally, in 2019 L. Wei and M. Yang tested the EKC by using a panel data set of 30 Chinese provinces during 2006–2015, studied the relationship between urbanization and economic growth through a simultaneous equation model. The results showed a positive effect of urbanization on economic growth through the accumulation of physical capital, knowledge capital, and human capital, while pollution revealed a significant inhibitory effect on urbanization. An inverted U-shaped relationship between economic growth and environmental pollution, and between urbanization and environmental pollution, has been confirmed by the analysis.

Literature review rejecting the EKC Theory

Another important part of the literature rejected the EKC theory. As regards CO_2, in 2006 Auffhammer and Carson, contrary to the previous researches carried out in 2000 and 2004, released a new one in which the EKC hypothesis and the flattening trend were rejected for CO_2 emissions. Indeed, the results demonstrated a positive increasing pattern, which stands for a negative effect of the economy on the environment. This publication was incredibly alarming inasmuch no conciliation was supposed to be possible between the environmental quality and the economic performance.[19]

In 2011 Halkos and Tzeremes published a new research on EKC for CO_2 emissions from 1965-2009 by employing data on a country level. According to their finding an inverted U-shaped relationship between variables exists. However, the result changed when a control variable, through which the influence of the industrial sector could be measured, has been introduced. Indeed, the relationship kept existing but with an N-shaped pattern. As a consequence of this discovery, the author stated that main inefficiencies on environment were due to a heavy industrialization.

Another research has been published by Cohen et al. in April 2018. The authors analyzed the Kuznets elasticities (the relationship between trend emissions and trend GDP) between GDP and CO_2, and other Greenhouse gases (GHG) of 29 Chinese provinces, during 1990-2012. According to the results, little evidence of decoupling[20] are present at the aggregate level, which means that GDP growth rate and environmental growth rate normally tend to increase at the same time. Such a finding means that economic development in the Republic of China is not naturally sustainable, even if elasticities in the last decades showed to be smaller than in the past (holding on the hope of further improving in the future). More specific insights were present when analyzing data at a provincial level: eastern provinces, which normally detain wealthier conditions, often reveal evidence of lower Kuznets elasticities with respect to southern and western provinces, which means that differences among regions are supposed to be present in China, and that poorest regions could suffer from economic and environmental relegation.

[20] In environmental economics, the notion of Decoupling refers to the phenomenon by which two variables show to follow independent growth rates. More specifically, absolute decoupling can be found when the GDP growth rate increase is followed by a gradual decrease in environmental degradation, on the contrary relative decoupling can be found in the case in which an increase trend of GDP is followed by a lower growing rate of environmental degradation.

In 2019, Debin Fang published a study which basically took into consideration the EKC between economic growth and CO emissions in China in the period between 1995 and 2016, hence introducing several variables, such as fixed capital investment, energy intensity, urbanization level, and trade openness. The results of the panel data analysis showed the support for an N-shaped curve between per capita CO emissions and per capita GDP in eastern, central, and western China. The main purpose of this study was to analyze spatial correlation dependencies in the EKC relationship between economic growth and CO_2 emission intensity, by introducing both geographic and non-geographic proximities. The main contribution of this research precisely was the introduction of economic distances. To this extent, a Spatial Auto-Regressive model (SAR) has been employed and different matrices have been tested (binary contiguity matrix, geographic weights matrix, economic weights matrix, geo-economic weights matrix and inverse geo-economic weights matrix). The results showed greater efficiency from the economic matrix, with respect to the geographical distances. Moreover, another important insight was the evidence of a N-shaped relationship between GDP per capita and CO_2 emission intensity.

Regarding $SO_{2,}$ in 2009 Wen and Cao tested EKC hypothesis for SO_2, waste water, waste gas, and solid waste, but no more information has been given with respect to the period and the geographical detail. The authors realized that environmental pressure could naturally be reduced only for some pollutants, while for some others, such as SO2, the economic development would necessarily lead towards worse environmental conditions. In this regard, indeed increasing demand for energy consume resulted in higher emissions, given that it is impossible to resolve environment issues originated by economic performance only by improving economic performance itself. As a result, China should consider following a corrective way towards sustainable economic development.

Another negative insight regarding the impact of SO_2 emission on environment has been given by Llorca and Meunié (2009). According to their research, the use of a fixed effects panel data model in 28 provinces explained the existence of an N-shaped curve. The same analysis carried out through a different model in which another test has been employed, resulted in a positive linear relationship, which means that the decrease of SO_2 emissions in China could not be related to EKC effect, but should probably be due to an exogenous public action.

K. Jayanthakumaran et al. in 2011 rejected the EKC theory for SO_2 emissions. Another interesting publication has been introduced by He in the same year. In this research, the author analyzed the role of industrial SO_2 emissions density in environmental degradation by using a panel data approach at the provincial level, in the period between 1991-2000. Its most important contribution has probably been the decomposition of income, scale, and composition effect, plus the introduction of the international trade as a control variable. The results of the observations demonstrated some important insights. Firstly, excluding from the database the largest cities under direct governmental control (Beijing, Tianjin and Shanghai), rather than an EKC pattern, an increasing trend in SO_2 emissions density, due to an income growth, seemed to be discovered. Secondly, the analysis on composition effect (K/L) lead to a controversial result, in fact despite its general expectations, this variable showed to act as a pollution-decreasing agent. Finally, more complex conclusions were reached regarding the role of international trade, as far as opposite effects were supposed to be present in trade: from one side, the trade intensity normally tended to increase pollutant emissions density as more production and transportation activities were necessary; on the other side, China still tended to conserve a comparative advantage in labor-intensive sectors in most of its provinces and, as a consequence, an increase in capitalistic ratio was supposed to be environmental-friendly. For this reason, openness in trade revealed to be sustainable for moderate-income provinces, while a negative repercussion on the environment was expected for low or high-income provinces.

In 2016 another research has been provided by Shostya. In this analysis a panel data model of 27 Chinese provinces during 2004-2013 has been employed in order to study the relationship between GDP and 3 air pollutants: PM, SO_2, and NO_2. Other control variables have been introduced in order to explain the rising levels of pollution, such as: urban population pressures, disposable income per capita, electricity production, and rise in vehicle ownership. The results demonstrated interesting insights, indeed the economic development affects in different ways every air pollutant, revealing a negative effect towards PM, and a positive effect towards both NO_2 and SO_2. Nonetheless, statistically significant results were present only in SO_2 estimators, which means that the model could suffer from some endogeneity problems.

Regarding other pollutants, in 2002 De Groot showed the exisence of a N-shape relationship between economic growth and solid wastes, and a non-significance effect between economic development and solid wastes.

In 2004 Shen and Hashimoto verified a N-shaped relationship for 2 pollutants (Dust fall, Industrial waste stock). Two years later, Shaw et al. demonstrated that the EKC hypothesis did not stand for NO_X, while Shen J. revealed a U-shaped pattern for SO_2 and no relationship regarding Dust Fall. In the same year, Ross and Song made a research over 30 Chinese provinces for 6 main polluters. The results demonstrated a general support of the EKC hypothesis, however it has been emphasized that more investments in the economic growth could not solve environmental degradation alone, therefore government still needed to stress on research and development, regulations, industrial structure change, and economic openness.

The same need has been reported by Chen (2007), whose study on Chinese environment conditions highlighted the impossibility to declare a certain availability of EKC hypothesis, due to many differences on the complicated relationship between environmental quality and income, which revealed to be deeply different basing on the types of pollutant agents and provinces.

In 2008 Auffhammer and Carson once again stressed on the inefficacy of actual environmental policies and on the importance to increase the efforts on the reduction of emissions and on the environment protection. In the same period, Jiang et al studied the EKC on waste gas from production and solid waste, but no statistical significance has been found regarding solid waste discharges and U-shaped pattern stood for per capita waste gas emissions and income.

Another research on EKC has been published by Song et al. in 2008. In this case, provincial data over 1985–2005 have been used in order to test the relationship between waste gas, waste water, solid wastes and GDP. Even if an inverted U-shaped pattern has been found for three main gas pollutants, the author stated that the increase in the economic growth could lead towards serious environmental issues, given that the turning points tended to appear at high levels of income and that only a few provinces already reached this stage.

In 2011 Xu and Song western region was characterized by a U-shaped curve. In 2015 H. Yang et al. studied the EKC relationship for seven pollutants basing on data of 29 Chinese provinces from 1995 to 2010. The results revealed that for any of the seven emission indicators the EKC hypothesis couldn't be considered valid. In fact, both the probabilities of obtaining a negative relationship or an inverted U-shaped curve have shown to be statistically below the level of 95%, which was taken as a critical level of analysis.

In 2016 Guo and Guo analyzed EKC relationship between GRP and $PM_{2.5}$ for several Chinese cities during 2013-2014. In their model other control variables have been introduced in order to mitigate the potential for misspecification and biased estimation and to better explain the phenomenon, such as: the proportion of secondary industry, the power generation, and the freight volume. The results provided evidence that both GRP and power generation were the cause of the increasing level of pollution, while freight volume was not supposed to affect $PM_{2.5}$ emissions. However, the presented model did not take into consideration a satisfactory time period (denoting the lack of long-term effects observations), and it was affected by the same issue of lack of reciprocity between variables' effects due to the single equation regression model. In the same year Stern and Zha published a research over 50 Chinese cities during 2013-2014. In this study, two different econometric models have been employed in order to analyze EKC relationship between economic development and $PM_{2.5}$, and PM_{10}. The results showed evidence of: negative time effects, convergence (concentrations falling faster in more highly polluted cities), ambiguous economic effect (namely: positive effect of growth on concentrations at high-income levels and a negative effect at low-income levels, even if it was not discovered any statistical significance for PM 10).

In 2017 Gu et al. published a research in which the EKC has been tested for per the capita industrial water use and the GDP of the eight economic zones, from 2002 to 2014. According to the results, evidence of a U-shaped relationship between industrial waste water and economic growth has been verified.

In March 2018 Wang W. published a new study about EKC, analyzing the relationship between the air quality index and the GDPPC by employing a traditional EKC model and two improved models. To this extent, a panel data of 41 major Chinese cities during 2000-2015 has been taken into consideration. The observation has been modelled in three different forms and each one of them gave different results, showing evidence of a U-shaped or N-shaped curve basing on the way in which the analysis has been conducted. Unfortunately, the study has been developed through the use of a pure EKC model, which is not the most suitable option and could be object of many critics.

<u>Miscellaneous results</u>

Some research was not able to univocally define the existence of the EKC, as far as the theory could be valid only for certain pollutants and not for others, or just because natural adjustment is not supposed to exist between the economic-environmental equilibrium, hence needing strong social and political actions.

In 2016 Li et al., published a research in which a dynamic panel data model[21] of 28 Chinese provinces from 1996 to 2012 has been developed. The observation took into consideration the relationship between economic development variable and three pollution agents variables (CO_2, industrial waste water, and industrial solid wastes), with the introduction of many control variables, namely: energy consumption, trade openness, and urbanization. The results demonstrated: at first, the support for EKC hypothesis for every pollutant and for every model and estimation method adopted; secondly a positive effect of energy consumption on pollution, positive effect of urbanization on pollution in the long run (in short run there was no evidence of positive effect). As a consequence, the authors recommended the introduction of environmental policies through which limitation of energy consumption and urbanization should be undertaken under control by the government, whenever the economy shows developing trends.

Another important research has been published by Zheng et al.in the same year. The observation has been carried out at a city level, taking into consideration data from 73 Chinese cities, during 2002-2012 by employing an extended STIRPAT[22] panel data model. The results demonstrated that population size, secondary industry proportion, energy consumption structure, urbanization level, and economic level positively influence CO_2 emissions (no statistical significance was present as regarded urbanization level). As far as regarded the EKC, evidence of its existence depended strongly on the clustering technique adopted.

In 2017, Y. Kim et al. tested the EKC hypothesis on SO_2, wastewater discharge and solid wastes, by employing a panel data set of 29 Chinese provinces in the period between 1994 and 2010. To this extent, it was introduced a Geographically Weighted Regression approach, by which each location has been weighted basing on its distance from the geographical regression points. The advantage of such a model is that a specific estimation could be run for each province, by taking into consideration spatial heterogeneity. The results pointed out a high variation in the confirmation of the EKC hypothesis, causing the necessity of very different policy recommendations for each province.

[21] A Dynamic Panel Data model is a model in which, similarly to autoregressive models, dependent variables are likely to be correlated in time. In order to handle the dynamicity of the model, lagged terms are introduced. Due to the endogeneity of lagged terms, biases and errors are normally produced by the estimators. In order to solve this issue, different estimators should be introduced. The most famous approaches are the Generalized Method of Moments (GMM), which can give estimations in the short-run, and the Auto-Regressive Distributed Lag (ARDL), which is more suitable to long-run estimations.

[22] STIRPAT model stands for: stochastic impact by regression on population, affluence, and technology.

In April 2018 on more contribution has been given. Li F. and Li Y. analyzed a data for 31 provincial economies from 1980 to 2015, finding out a long-term cointegrated relationship between economic and environmental data. According to the results, the turning point hasn't occurred yet in China, which means that Chinese government should keep stressing on environmental policies in order to solve the issue. Moreover, the author stated that the Chinese situation should be treated very carefully, given that there is no guarantee for the developer country to be able to follow the same steps of the developed countries in which EKC revealed evidence.

In 2018 G. Du et al. examined the relationship between economic growth and haze pollution, and the relative turning points for different regions basing on the panel data of 27 Chinese capital cities and municipalities in the period between 2011 and 2015. The results showed differences across regions, indeed a U-shaped relationship was supposed to hold for the central region, while different evidence has been revealed in support of inverted N-shaped relationships for eastern, western, and northeastern regions.

In 2019 Wang Z. et al analyzed the EKC related to seawater quality, by employing a multiple logistic regression model. The research showed the impacts of socio-economic development on mainland China's coastal waters. The results basically revealed better levels of seawater's quality in the regions in which industrial adjustment has previously been introduced.

Data and variables

In this section will be discussed the origin, the preprocessing and the forecast of data gathered and of the variables selected, in order to develop the analysis. The research will take into consideration the official data from 22 Chinese provinces (Hebei, Shanxi. Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, and Qinghai), 5 autonomous regions (Guangxi, Inner Mongolia, Ningxia, Xinjiang, and Tibet), and 4 municipalities (Beijing, Shanghai, Chongqing, and Tianjin), during 1999-2018.

Data Origin

1. Population: official data about the total number of the resident Chinese population at the year-end (10.000 persons) is provided by *China Statistical Yearbook* at a provincial level[23], from 1999 to 2018. Data is assumed to be correct and no need of adjustment is required for this research[24].

   Population has been frequently used as a control variable in the literature. Basing on the model employed in the analysis, its effect can differ. The expectations could foresee both a positive and a negative effect on the environment. The positive effect could be due to the fact that higher population density normally requires higher levels of resources and energy consumption, hence resulting in environment degradation (Scale Effect). On the contrary, higher population density could create more social concern, hence resulting in the establishment of more stringent environment regulations, which should normally reduce the environmental pressure. (S.F. Wang et al. 2015).

2. Real Gross Regional Product Per Capita (Real GRPPC): official data about the Chinese economic performance (*Gross Regional Product, 100 million Yuan)* at a provincial level is provided by *China Statistical Yearbook*, from 1999 to 2018. When analyzing economical time series, inflation[25] effect through years is one of the main causes of biased estimations, because of this

[23] As provincial level is meant the set of provinces, autonomous regions, and municipalities.

[25] The Inflation is a persistent rise in the general price level sustained in time. This economical phenomenon could deeply affect the stability of a country's economy: usually countries that experience highly-variable rates of inflation

reason it is necessary to adjust *normal GRP* for price variations, and to find out the *real GRP*[26] (1.1). To this extent, the *Consumer Price Index* (CPI)[27], provided by the same official sources at the provincial level, has been employed, taking into consideration 1997 as a base year (CPI_{1997} = 100) (1.2). As far as CPI is normally calculated on average variations, basing on prices and quantities for a wide variety of different product and service categories, the expenditure approach[28] has been employed in GRP observations, in order to have an higher accuracy in the adjustment process. Once that real provincial GRP has been estimated, data has been divided by the amount of population in that area, hence resulting in the estimation of the real GRPPC, which has been employed as an important economic development index in this research (1.3). The main information provided by this variable is the value level of products and services averagely produced and available in a single economy per person. It is supposed that higher the average value, higher the level of economic development, given that people could benefit from more products and services, hence potentially living in better conditions.

$$RGRP_{i,t} = GRP_{i,t} - \left(i * GRP_{(i,t-1)} \right) \tag{1.1}$$

$$i_{i,t} = CPI_{i,t+1} - 100 \tag{1.2}$$

$$RGRPPC_{i,t} = \frac{RGRP_{i,t}}{POP_{i,t}} \tag{1.3}$$

Where:
- RGRP is the Real Gross Regional Product (100 mln Yuan);
- GRP is the Gross Regional Product (100 mln Yuan);
- i is the Inflation Rate (%);
- CPI is the Consumer Price Index (base 1997=100);
- RGRPPC is the Real Gross Regional Product Per Capita (Yuan/Person)
- POP is the Population (n. of people).

are not considered to have a stable economy. In contrast, deflation is a continuous fall in the average price level while disinflation is a decrease in the rate of inflation.

[26] Real GRP: is the GRP adjusted by inflation rate. The indicator points out the real purchasing power of consumers.

[27] Consumer Price Index: is an index which synthetize the average level of the prices for various goods.

[28] The Expenditure Approach: takes into consideration several spending activities including consumer consumption, investing, government spending, and net exports, in order to calculate GDP.

3. Sulphur Dioxide (SO_2): official data about total *Sulphur Dioxide emissions (tons)* is provided by *China Statistical Yearbook* at a provincial level, from 1999 to 2018. Data have been assumed to be correct and no need of adjustment was required for this research.

4. Particulate Matters 2.5 ($PM_{2.5}$): official data about *Particulate Matters average concentration with a diameter of 2.5 µm or less* is provided by *The OECD database* at a provincial level from 1999 to 2015. In the dataset provided, data are missing for the year 2014, while data from 2015 are estimated values. In order to fulfill the missing values, interpolation has been employed, through the calculation of the mean of the values between 2015 and 2013.

5. Industrial Waste Water (WW): official data about total *Sulphur Dioxide emissions (tons)* is provided by *China Statistical Yearbook* at a provincial level, from 2004 to 2016. Data have been assumed to be correct and no need of adjustment was required for this research

6. Carbon Dioxide (CO_2): as far as regards *Carbon Dioxide (Mt)*, official data are missing, so the IPCC (Intergovernmental Panel on Climate Change) framework has been employed in order to compute estimated values. In this regard, data provided by *The Chinese Energy Statistical Yearbook* have been used, by taking into consideration the *consumption (10000 tons) of 8 main energy sources*[29] at a provincial level from 1999 to 2016. Some energy consumption data are

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[29] Coal: hard, black substance that is dug from the earth in pieces, and can be burned to produce heat. (Cambridge Dictionary);

Coke: a solid, grey substance that is burned as a fuel, left after coal is heated and the gas and tar removed (Cambridge Dictionary);

Crude Oil: Crude oil is a mineral oil consisting of a mixture of hydrocarbons of natural origin, being yellow to black in color, of variable density and viscosity. (IPCC Guidelines);

Gasoline: refined petroleum used as fuel for internal combustion engines. (Oxford Dictionary)

Kerosene: Kerosene comprises refined petroleum distillate intermediate in volatility between gasoline and gas/diesel oil. (IPCC guidelines);

Diesel Oil: diesel oil includes heavy gas oils. Gas oils are obtained from the lowest fraction from atmospheric distillation of crude oil, while heavy gas oils are obtained by vacuum predistillations of the residual from atmospheric distillation. Several grades are available depending on uses: diesel oil for diesel compression ignition (cars, trucks, marine, etc.), light heating oil for industrial and commercial uses, and other gas oil including heavy gas oils. (IPCC Guidelines);

Fuel Oil: This heading defines oils that make up the distillation residue. It comprises all residual fuel oils, including those obtained by blending. (IPCC Guidelines);

missing completely at random, so the interpolation method through the mean of the surrounding values has been applied once again. Due to data availability limitations, Tier 2 approach has been followed in the construction of the emission inventory, as follows:

$$Emissions_{GHG} = \sum_{Fuels} Emissions_{GHG,fuel} \tag{1.4}$$

Where:
- $Emissions_{GHG}$ are the total emissions of the Greenhouse gas;
- $Emissions_{GHG,fuel}$ are the emissions of the Greenhouse gas for the single energy source.

This approach is nothing but the result of the combination between activity data (energy consumption) and the emission factors (which is basically an estimated value that express the emission-activity ratio) (1.5). This approach is based on the law of energy conservation and It is basically defined as a Bottom-Up approach. It differs from satellite monitoring, which can be categorized as a Top-Down approach. At first, is necessary to compute the *Net Calorific Value (NCV's)* of every energy source, which is basically the amount of energy content from every source and can be determined by measuring the heat produced by a certain quantity of it. NCV's data are provided by the IPCC Guidelines, which normally express average values and a confidence interval. In this research average NCV's values are taken into consideration. Combining NCV's and energy sources, the total energy produced can be calculated (J).

$$Energy_{fuel} = Mass_{fuel} * NCV_{fuel} \tag{1.5}$$

Where:
- $Energy_{fuel}$ is the energy produced (TJ)
- $Mass_{fuel}$ is the mass of energy source (Gg)
- NCV_{fuel} is the net Calorific Value of the energy source (TJ/Gg)

The second step is the calculation of the *Emission Factors (EF's)*. The EF can be conceived as the combination of the carbon content of the energy source, the carbon oxidation rate (the standard value is 1, which basically means that during the combustion process, no

Natural Gas: Natural gas should include blended natural gas (sometimes also referred to as Town Gas or City Gas), a high calorific value gas obtained as a blend of natural gas with other gases derived from other primary products, and usually distributed through the natural gas grid. (IPCC Guidelines) carbon atom is left aside) and the CO_2 carbon molecule mass ratio (which is 44/12 g/mol[30], that is to say that 3,67g of CO_2 are produced every 1g of carbon burned).

$$EF_{fuel} = \sum_{fuels} \left(\frac{CC_{fuel} * O * 44}{12} \right) \tag{1.6}$$

Where:
- EF_{fuel} is the emission factor (Kg/TJ)
- CC_{fuel} is the Carbon Content (Kg/GJ)
- O is the carbon oxidation

According to a research carried out by Deng et al. in 2015, Chinese coal has been proved to be lower in quality with respect to the standards adopted in the IPCC guide. Indeed, by taking into consideration almost 602 carbon samples in 4243 coal mines, the analysis pointed out a different substantial composition for this energy source, which is basically poorer in carbon content and richer in ash. As a consequence, for a fixed amount of material, Chinese carbon is able to release less power when burned, with respect to higher quality carbon types, and releases more ash, hence increasing the amount of $PM_{2.5}$ concentration in the air. Basing on such a research, the calculated Coal EF has been reduced by 40% in order to better represent its own quality in China.
In order to check the accuracy of the calculation of CO_2 Emissions in China, total values have been compared with The World Bank official data (Fig.1). The results show a good accuracy and for this reason data are supposed to be reliable for the aim of this research.

[30] The molecular mass is the sum of singular atoms masses, multiplied by the relative number of atoms:

- Carbon atom mass = 12 g/mol
- Oxygen atom mass = 16 g/mol

$$C + O2 = CO2$$

- CO2 molecular mass = (12*1) + (16*2) = 44

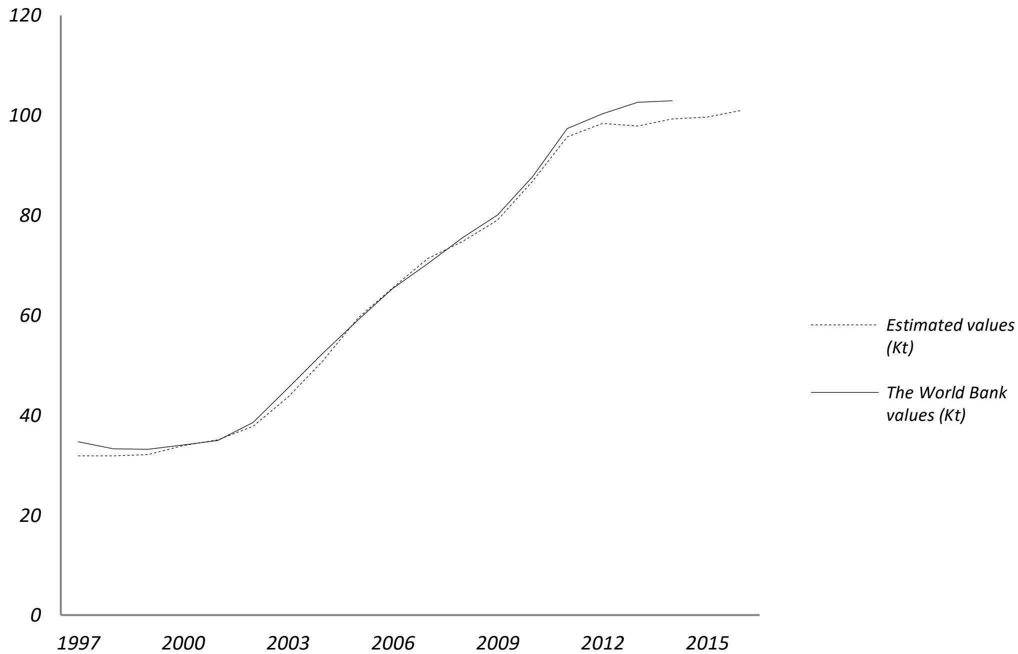

Fig.4 Shows the difference between *CO2 Emissions (100000 Kt)* estimated values computed through the described process and the official national data provided by The World Bank.

7. Foreign Direct Investments (FDI): data about Foreign Direct investments is provided by the *China Statistical Yearbook* at a provincial level, from 1999 to 2018. In order to take into consideration this variable, *Total Investment of Foreign Funded Enterprises*[31] *(USD million)* data has been adopted and no need of adjustment is required for the aim of this research. The variable has already been introduced by other authors, such as J. Liu et al. (2019). The expectation is that a great concentration of FDI could stimulate the investments of pollutant production sites in developing countries, as a result of profitable outsourcing strategies pursued by developed countries (Pollution Heaven theory). In fact, poorer countries are normally characterized by lower production costs (labor in particular) and lower environmental stringency.

8. Trade Openness (TO): The *Trade Openness index* is basically an index calculated through the ratio between the Total Trade (Import and Export) and Total Real Gross Regional Product (RGRP). In order to calculate this index, data about Import, Export and GRP have been

collected by *China Statistical Yearbook* at a provincial level, from 1999 to 2018. To this extent, *"Total Value of Imports and Exports of operating units(1,000 US dollars)"* and *"Total Value of Exports of operating units(1,000 US dollars)"* have been adopted [32], while Real GRP has been converted from Yuan to USD (average yearly exchange rate has been calculated from 1997 to 2016, monthly data are provided by The Federal Reserve Bank).

$$TO_{it} = \frac{(X_{it} + M_{it})}{RGRP_{it}} * 100 \tag{1.7}$$

Where:
- TO is the Trade Openness (%)
- X is the Export (1000 bln USD)
- M is the Import (1000 bln USD)
- RGRP is the Real Gross Regional Product (1000 bln USD)

Trade openness is a good index of the impact of trade in an economy, in fact it gives the indication of the dependence of domestic producers on foreign markets, and of foreign consumers on the domestic supply. Normally per capita income and trade openness are supposed to be correlated: the more the level of trade openness rises, the more capita income increases, but following a decreasing path in time (*Online Trade Outcomes Indicators – The world Bank, 2013)*. Evidence of positive correlations have been shoved also between TO and Productivity, basing this theory on the main assumption that an opened market causes the spread of the competition, resulting hence in a higher output/input relationship *(JaeBin Ahn and Romain Duval, 2017).* Despite these phenomena, the introduction of the Trade Openness index is not new, for instance it can be found in the research carried out by J. He and H. Wang in 2012. The expectation is strictly related to the one presented for FDI. In fact, given the above described incentivizing mechanism for outsourcing a production chain to developing countries, it can be expected that then the output would be traded with other economies. This phenomenon seems to particularly fit Chinese economic model, which is the first exporter in the world. The main concern is that China could have gained high trade margins by exploiting its competitive advantage in pollution intensive goods. Moreover, it has to be considered the role of the logistic sector, which is supposed to require high levels of energy consumption for transportation.

9. Energy Intensity (EI): Energy Intensity Index has been calculated through the adoption of total *Power Generation (100 mln kwh)* data, directly provided by *China Statistical Yearbook* at a provincial level, from 1999 to 2018 (Missing values are interpolated through the mean values). Given that EI is supposed to be an efficiency index, data has been divided by the RGRP, in order to follow the typical Input/output framework. The index is actually calculating the amount of power (Kwh) produced by each unit of Real Gross Regional Product (Yuan).

$$EI_{it} = \frac{PW_{i,t}}{RGRP_{i,t}} * 100 \tag{1.8}$$

Where:
- EI is the Energy Intensity (Kwh/ Yuan)
- PW is the Power Generated (100 mln Kwh)
- RGRP is the Real Gross Regional Product (100 mln yuan)

The introduction of the EI index could be already found in other researches, such as the one carried out by G. Du et al in 2018. The expectation in this case is given to the energy sector composition characteristics in China. In fact, as far as the main energy source has been for many years the low-quality coal, a high EI ratio could give the measure of the importance of the impact of energy (especially dirty energy) on the economy. If the ratio is low, the efficiency of the energy sector is meant to be high, hence resulting in higher environment quality. This index I meant to measure the Technique Effect, which is the effect of a different production technique on the environmental quality.

10. Industrial Capital - Labor Ratio (KL): data about Capital and Labor are provided by *China Statistical Yearbook* at a provincial level, from 1999 to 2018. In particular, *Total Value of*

Industrial Fixed Assets (100 mln Yuan)[33] and *Total Wage Bill of Employed persons in Urban units (100 mln Yuan)* have been introduced in order to compute the index.

$$KL_{i,t} = \frac{K_{i,t}}{L_{i,t}} * 100 \tag{1.9}$$

Where:
- KL is the Industrial Capital Labor Ratio (%)
- K is the amount of Industrial Capital (100 mln Yuan)
- L is the amount of Labor (100 mln Yuan)

As far as regards the Capital-Labor Rario, the variable has already been used by J. He and H. wang in 2012. The expectation is that contrarily to the Pollution Heaven theory, by which China could be expected to specialize in pollution intensive industries, the extremely rich endowment in labor force suggests the specialization in less-polluting industries (basing on the comparative advantage hypothesis). This can be used as an index to measure the Composition Effect, which is the share of dirty goods on the total output, basing on the assumption that higher capital intensity should lead to more-pollution intensity industries.

[33] Total Value of Fixed Assets refer to tangible assets that an enterprise held for the production of goods and provision of services, for rental or administrative purposes whose serving life is more than one fiscal year. It includes houses, buildings, machinery, transport equipment and other production, of whose serving life is more than one-year period, and business-related equipment, appliances, tools, etc. Total value of fixed assets is a time-point indicator, referring the ending balance after deducting depreciation and impairment from fixed assets. For enterprises performing "Enterprise Accounting Standards", data on this item can be obtained from the ending figures on fixed assets from the assets and liability table of enterprise.

Econometric Model - Three Stage Least Squares - Geographically Weighted Panel Data Regression (3SLS – GWPR)

In this research a Three-Stage Least Squares - Geographically Weighted Panel Data Regression model (3SLS - GWPR) will be adopted. The procedure is parametric in its nature and it normally requires a priori definition of parameters, which have to be statistically tested and fitted with empirical data. GWPR is based on local panel estimates using weighted data for subsamples of nearest locations and is the result of a combination between Panel Data and Geographically weighted analysis. The analysis has been conceived in order to allow for the study of simultaneous equations, so the model will be improved through the implementation of the Three-Stage Least Squares procedure (3SLS). The definition of the model will start at first with an overview of the general Panel Data model, secondly the geographical weighting procedure will be introduced, finally the 3SLS model will be implemented and fitted to Panel Data analysis. Every model exposed in this research is linear in its nature[34].

General Panel Data model

A Panel Data regression differs from a regular time-series or cross-section regression in that it has a double dimension on its variables, in this sense, it combines the features of both methods. A general Panel Data model can be expressed as follows:

$$y_{it} = \alpha + \beta x_{it} + u_{it} \qquad i = 1,...,N; \quad t = 1,...,T \tag{2.1}$$

where i denotes the individuals (cross-section dimension), t denotes the time (time-series dimension), x_{it} are the observations on K explanatory variables, α is a constant, β is the parameter to be estimated and u_{it} are the idiosyncratic error terms[35]. For the aim of this analysis, a balanced

[34] Linear models can foresee exponential terms in its independent variables, while estimators and coefficients are always linear.

[35] Idiosyncratic error terms: In panel-data models, the idiosyncratic error term refers to the observation-specific zero-mean random-error term. The error terms can be analyzed in two different ways:

The One-Way error model:
$u_{it} = v_i + \varepsilon_{it}$ i = 1,...,N; t = 1,...,T

Panel Data set will be used, which is to say that each individual i is observed in all time periods t.

In modern Econometrics, Panel Data models can foresee Fixed or Random effects, where "Random-Effect'" is synonymous with zero correlation between the observed explanatory variables and the unobserved effect, "Fixed-Effect" normally allows for arbitrary correlation between the unobserved heterogeneity and the observed explanatory variables. The Random-Effects analysis foresees the inclusion of v_i into the error term (u_{it}), which is an individual specific component that does not vary over time, and a remainder component (ε_{it}), which is assumed to be uncorrelated over time. This is to say that all correlation of the error terms over time is attributed to the individual effects. In the Fixed-Effects approach, the only hypotheses made about the individual-specific effects is that they exist.

The Between transformation: consists in the creation of a cross-sectional data set by taking into consideration the time-averages for each individual from the (2.1), and then running an OLS regression. The Within transformation: consists in averaging the (2.1) over time and then subtracting the averages values from the original values of the same equation. The model basically analyzes the variations about the mean of the dependent variable in terms of the variations about the means of the explanatory. The estimator shows the time-series information, which reflects the within individuals changes across time.

Geographically Weighted Panel Data Regression

Contrary to the global Panel Data model, the GWPR model operates on subsamples of weighted data, allowing for the study of estimates across space and providing results for each singular individual. In order to obtain local estimates for a single location i, the data around it will have to be properly weighted after defining the number of locations that are going to be subsampled (bandwidth). To this extent Kernel functions are used to create weight matrixes, which are to be applied to each individual at all time periods. Given the Kernel weighting function:

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where v_i denotes the unobservable individual-specific effects and ε_{it} denotes the remainder stochastic disturbance term.

The Two-Ways error model:

$$u_{it} = v_i + \lambda_t + \varepsilon_{it} \qquad i = 1,...,N; \quad t = 1,...,T$$

where v_i denotes the unobservable individual effect, λ_t denotes the unobservable time-effect and ε_{it} is the remainder stochastic disturbance term.

$$w_{ij} = \begin{Bmatrix} \left[1 - \left(\frac{d_{ij}}{h_i}\right)\right]^2 & if \quad d_{ij} < h_i \\ \\ 0 & otherwise \end{Bmatrix} \tag{2.2}$$

Where i is the target individual, j are all the individuals in the subsample, d is the distance between individuals, h is the distance at which the weights are set to zero. The weighted subsample is the result of the multiplication between the single weights and the original sample:

$$W = \left(x_{ij} * w_{ij}\right)^T = [\quad x_{i,1} \quad x_{i,2} \quad \dots \quad x_{i,j} \quad \dots \quad x_{i,N} \quad] \begin{bmatrix} w_{i,1} & 0 & 0 & \cdots & 0 \\ 0 & w_{i,2} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & w_{i,j} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & w_{i,N} \end{bmatrix} = \begin{bmatrix} W_{i,1} \\ W_{i,2} \\ \vdots \\ W_{i,j} \\ \vdots \\ W_{i,N} \end{bmatrix}$$

Where i is the target individual, j are all the individuals in the subsample, W is the diagonal matrix of the single weights and X is the vector of the single empirical values. The utilization of a bisquare function allows for the definition of the subsample without further operations, in fact, the values which are more distant than h_i are automatically set to zero. Once the weighting is applied, the Panel Data regression can be estimated to obtain local estimations. The global weighted Panel Data model can be expressed in the matrix form as follows:

$$y_{it} = \alpha + \beta w_{it} + u_{it} \qquad i = 1,...,N; \quad t = 1,...,T \tag{2.3}$$

Where w_{it} are the weighted observations on K explanatory variables. Finally, in order to obtain the complete set of local estimations is necessary to apply the same procedure to each individual. In the definition of a GWPR model there are two important factors to be considered, namely the definition of the Kernel function type which has to be employed and the definition of its bandwidth. While the definition of the Kernel function type is not highly relevant, the definition of the bandwidth could potentially affect the results of the analysis. The bandwidth can be fixed or adaptative, basing on if it is conceived to adapt itself and allow the length of the Kernel for covering a defined number of individuals (adaptative) whether if a precise numeric length is defined a priori (fixed). For the aim of this research, an adaptive bisquare weighting function is preferred (F. Bruna and D. Yu - 2016).

Simultaneous Equation Model

In order to face the simultaneity issue, a Three-Stage least Squares model has been employed. The 3SLS is a specific form of Seemingly Unrelated Regression model (SUR)[36], it is a full information method[37] and is composed by 3 steps:

- First-stage regression: each equation of the structural form equations[38] of the model is first estimated independently using the 2SLS estimator, obtaining a consistent estimate of all the coefficients and the corresponding residuals.

$$\hat{\Xi} = (\hat{\epsilon}_1, \hat{\epsilon}_2, \dots \hat{\epsilon}_n) \tag{2.4}$$

Where $\hat{\epsilon}$ are the estimated residuals.

- Second-stage covariance matrix estimation: the residuals are used to estimate the element of the covariance matrix of errors.

$$\hat{\delta}_{i,j} = (\hat{\epsilon}_i{}^T \hat{\epsilon}_j)\mathrm{T}^{-1} \tag{2.5}$$

Where T is the time period. In the same way, the covariance matrix of errors $\hat{\Sigma}$ can be expressed as:

$$\hat{\Sigma} = (\hat{\Xi}^T \hat{\Xi})\mathrm{T}^{-1} \tag{2.6}$$

[36] Seemingly Unrelated Regression model: is a model in which equations seems to be completely independent and unrelated to each other, even if correlation can be found due to the disturbances.

[37] Full Information method: foresees the estimation of coefficients by taking into account all the single equations at the same time. On the contrary, the method by which each single equation is analyzed by its own is defined as “Limited Information method”.

38 Structural Form: a Structural System of Equation (SEM) expresses each function by setting the endogenous variables as dependent variables, and the direct causes as independent variables.

- <u>Third-stage regression:</u> the model is transformed by $\widehat{\sum}^{-1}(X(X^T X)^{-1})X^T$, and finally the instrumental variables estimator is applied to the transformed system. The best estimator is:

$$\hat{\beta}_{3SLS} = \ (\hat{Z}^T \left(\widehat{\sum}^{-1} \otimes W(W^T W)^{-1} W^T Y\right) \hat{Z})^{-1} \ \hat{Z}^T (\widehat{\sum}^{-1} \otimes W(W^T W)^{-1} W^T Y)\, Y \qquad (2.7)$$

Which variance can be expressed as:

$$Var\left(\hat{\beta}_{3SLS}\right) = \left[\hat{Z}^T \left(\widehat{\sum}^{-1} \otimes W(W^T W)^{-1} W^T\right) \hat{Z}\right]^{-1} \qquad (2.8)$$

The process can be repeated iteratively, by calculating each time a new covariance matrix of errors, which is every time more accurate. Iteration can continue till convergence.

A deep technical description of R functions used in order to employ the econometric model is showed in Appendix II.

Results

In order to assess the validity of the EKC theory in China, the GWPR model has been applied to each province, with a bandwidth that covers the 80% of the regions. The analysis has been carried out through the implementation of a R code, which takes inspiration by Y. Coissant et al. (2019). The endogeneity issue, which is due to the presumed simultaneity[39] between economic development index and environment quality index, has been taken into consideration through the implementation of an instrumental variables[40] estimator. The instrumental variables estimator is computed using the plm function. The instruments are specified with a two-part formula, where the first part indicates the covariates of the model and the second part points out the instruments. A set of variables has been exposed in a simultaneous equation system composed by two equations, as follows:

$$EQI = \alpha + \beta_0 + \beta_1 \ ln(RGRPPC) + \beta_2 \ ln(RGRPPC)^2 + \beta_3 \ ln(RGRPPC)^3 \mid lag\ (Z_1) \qquad (2.9)$$

$$RGRPPC = \alpha + \beta \ ln(EQI) \mid lag\ (Z_2) \qquad (3.0)$$

Where EQI is the Environmental Quality Index and Z is the following set of instruments:

$$Z_1 = \ln(RGRPPC) + ln(RGRPPC)^2 + ln(RGRPPC)^3 + \ln(\mathrm{POP}) + \ln(\mathrm{FDI}) + \ln(\mathrm{TO}) + \ln(\mathrm{EI}) + \ln(KL) \qquad (3.1)$$

$$Z_2 = ln(EQ) + ln(K) + ln(L) \qquad (3.2)$$

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[39] Simultaneity: In this case, there is an explanatory variable that is set simultaneously with the response. One clear example could be the analysis of demand and supply curves, which jointly are determined by the price, which is therefore endogenous.

[40] Instrumental variables: are exogenous and relevant variables.

- Exogeneity: is shown when the variable is uncorrelated with the disturbances;
- Relevance: is shown when the variable is correlated with the independent variable.

Finding instrument could be very challenging, in fact normally is very hard to satisfy both the requirements. One of the most diffused techniques is to introduce lag values of the exogenous variables, relying on the idea that events in the past cannot prodce direct effects to the disturbances in the future periods. Even if, very recently, this theory has been criticized, as it seems to produce biased estimations, in this research it has been employed.

Z_1 is the instrumental variables equation, it takes into consideration all the variables which are expected to produce effects on the EQ. Z_1 instead is the modified Cobb-Douglas production function. Equations (4.1) and (4.2) are firstly estimated independently using the instrumental variables estimators Z_1 and Z_2. Secondly, starting from this estimation a matrix of residuals and its relative error covariance matrix is computed. This matrix is then used in order to transform the variables, obtaining a transformed system. Finally, the computation of the estimator is carried out.

Natural logarithms have been applied to all the variables in order to make sure that the relationship between them is linear. In fact, the econometric techniques employed in this research have been strictly conceived for linear models.

The results of the analysis show great heterogeneity at a regional level, depending also on the pollutant/GHG. In the following table (1.1), the results are shown for each region and for each pollutant/GHG. The results report both the effect of economic development on the environmental quality index and the effect of the Pollutant/GHG on the economic quality index.

Table 1.1

		Simultaneous Equation - Geographically Panel Data Regression (SE - GWPR)			
		CO2 1999 - 2016	**SO2** 2000 - 2016	**PM2.5** 1999 - 2015	**WW** 2004 - 2016
Anhui	Intercept	-0.0564899	-0.077833	0.03411	-0.097847
	RGRPPC	1.0277318	5.681275 **	-0.390354	5.672278 .
	RGRPPC2	-0.0712544	-0.662374 .	0.444133 .	-0.722015
	RGRPPC3	0.0020983	0.02289	-0.035965 .	0.027691
	Pollutant/GHG	1.966654 ***	0.767564 ***	2.64164 ***	0.858678 ***
Beijing	Intercept	-0.0489718	0.059474	0.0195156	-0.020101
	RGRPPC	1.1218391 ***	-1.119455	0.6134107 **	-3.053294
	RGRPPC2	-0.1135626 **	0.633536 **	-0.1245686	0.858904
	RGRPPC3	0.0055088 **	-0.038808 ***	0.0080725	-0.043401
	Pollutant/GHG	1.851338 ***	0.753204 ***	2.6216527 ***	0.854214 ***
Chongqing	Intercept	-0.0328009	-0.016539	0.0092259	0.037502
	RGRPPC	0.3056461 *	5.571875 ***	0.6372648 *	5.128343
	RGRPPC2	0.041343	-0.679869 *	-0.1382135	-0.796209
	RGRPPC3	-0.0019777	0.02546 .	0.0095415	0.039504
	Pollutant/GHG	1.924127 ***	0.749927 ***	2.576114 ***	0.861096 ***
Fujian	Intercept	-0.0910404 .	-0.053008	0.037277	-0.165954
	RGRPPC	0.0545487	6.526409 ***	-0.45303	6.151522 **
	RGRPPC2	0.1061628	-0.852565 *	0.481757 .	-0.819197 *

	RGRPPC3	-0.0058514 .	0.033315 .	-0.039295 .	0.032727
	Pollutant/GHG	1.919773 ***	0.7735525 ***	2.638626 ***	0.8456685 ***
Gansu	Intercept	-0.0267344	-0.014632	0.061549	0.0099409
	RGRPPC	0.7340978 ***	0.768247	1.737857 .	-0.6677078
	RGRPPC2	-0.0409025	0.296174	-0.75586	0.3490192
	RGRPPC3	0.0021553 .	-0.023823 .	0.053282	-0.0166089
	Pollutant/GHG	1.843175 ***	0.7528639 ***	2.579014 ***	0.8595145 ***
Guangdong	Intercept	-0.1089862 *	0.00095274	0.0021109	-0.131106
	RGRPPC	0.3572407 ***	5.72672752 ***	0.6053727	1.034001
	RGRPPC2	0.0346352 .	-0.69846561 *	-0.1127122	0.134968
	RGRPPC3	-0.0017277 .	0.02577959	0.0066856	-0.011607
	Pollutant/GHG	1.888508 ***	0.7792926	2.63294 ***	0.852751 ***
Guangxi	Intercept	-0.09707896 *	0.018577	-0.017981	-0.075129
	RGRPPC	0.3718413 ***	5.364631 ***	1.11416 **	-1.582018
	RGRPPC2	0.02975019	-0.625802 *	-0.398341 *	0.606894
	RGRPPC3	-0.00139202	0.022089	0.02879 .	-0.032816
	Pollutant/GHG	1.888219 ***	0.7761271 ***	2.614866 ***	0.864632 ***
Guizhou	Intercept	-0.0848471 .	0.0099775	-0.016655	-0.056208
	RGRPPC	0.3690909 *	5.4454205 ***	1.171398 ***	-2.646146
	RGRPPC2	0.0297685	-0.6437653 *	-0.431406 *	0.798243
	RGRPPC3	-0.0013635	0.0230743 .	0.031344 *	-0.041373
	Pollutant/GHG	1.887151 ***	0.768843 ***	2.5986491 ***	0.8690201 ***
Hainan	Intercept	-0.086379 *	0.023002	-0.013749	-0.053409
	RGRPPC	0.3573904 **	5.064942 **	1.065246 **	-1.799108
	RGRPPC2	0.031987	-0.565792 .	-0.370658	0.629427
	RGRPPC3	-0.0014766	0.019086	0.026675	-0.033004
	Pollutant/GHG	1.890051 ***	0.777755	2.612907 ***	0.8632432 ***
Hebei	Intercept	-0.1048387 .	0.040123	0.057839	-0.0077648
	RGRPPC	1.8072128 ***	-0.847717	1.136094 ***	-7.4110983
	RGRPPC2	-0.2482612 ***	0.63025 .	-0.41807 *	1.7291121
	RGRPPC3	0.0121941 **	-0.041087 *	0.029399 *	-0.0866968
	Pollutant/GHG	1.829768 ***	0.78314 **	2.650596 ***	0.855229 ***
Heilongjiang	Intercept	-0.0344442	0.03382	0.0029337	-0.0187507
	RGRPPC	2.5014874 ***	-4.790876 **	1.1474415 ***	1.4034515
	RGRPPC2	-0.3921612 ***	1.410155 ***	-0.4181745 **	-0.0015413
	RGRPPC3	0.0194964 ***	-0.079527 ***	0.0296847	-0.0019918
	Pollutant/GHG	1.874572 ***	0.7644158 ***	2.630744 ***	0.8511467 ***
Henan	Intercept	-0.0172495	-0.051451	0.10352887	0.0061835
	RGRPPC	0.7059053	3.4342459 .	0.43230744	-4.0687911
	RGRPPC2	-0.040005	-0.2292535	-0.02857043	1.1397628 .
	RGRPPC3	0.0021352	0.0020423	0.00017766	-0.0611381 .
	Pollutant/GHG	1.9008 ***	0.786316 ***	2.712795 ***	0.867938 ***
Hubei	Intercept	-0.0397308	-0.092637	0.077911 .	-0.058277

	RGRPPC	-1.0048645	5.571058 ***	0.045951	-0.19839
	RGRPPC2	0.3144317 *	-0.666317 *	0.18586	0.38326
	RGRPPC3	-0.0160883 *	0.024355	-0.015161	-0.024196
	Pollutant/GHG	1.92965 ***	0.79392 ***	2.736207 ***	0.861676 ***
Hunan	Intercept	-0.1078904 *	-0.031617	0.0381285	-0.167776
	RGRPPC	0.2251656 .	6.191022 ***	0.211588	0.902864
	RGRPPC2	0.0628037 *	-0.794715 **	0.1039326	0.165237
	RGRPPC3	-0.0032093 *	0.030797 *	-0.0097957	-0.01324
	Pollutant/GHG	1.88936 ***	0.78124 ***	2.664526 ***	0.847738 ***
Inner Mongolia	Intercept	-0.026068	0.0808853	0.0220976	-0.0197778
	RGRPPC	1.0494694 ***	-1.1606754	0.7848607 ***	1.0967038
	RGRPPC2	-0.1003062 **	0.6393798 ***	-0.2208088 .	0.0586641
	RGRPPC3	0.0048803 **	-0.0390486 ***	0.015211	-0.0049538
	Pollutant/GHG	1.860466 ***	0.753181 ***	2.601687 ***	0.8562191 ***
Jiangsu	Intercept	-0.0414447	-0.0771905	0.0132363	-0.052691
	RGRPPC	1.9684529 *	3.1898395 .	0.2708092	3.504431
	RGRPPC2	-0.2625584	-0.1553329	0.0721743	-0.323144
	RGRPPC3	0.0117629	-0.0027623	-0.0072628	0.009375
	Pollutant/GHG	1.964918 ***	0.766532 ***	2.628858 ***	0.8634001 ***
Jiangxi	Intercept	-0.0940024 .	-0.059149	0.041616	-0.170784
	RGRPPC	-0.1732083	6.919021 ***	-0.347992	5.499215 *
	RGRPPC2	0.1554128 *	-0.930034 **	0.420497 .	-0.693262
	RGRPPC3	-0.0084766 *	0.037126 *	-0.034330 .	0.026671
	Pollutant/GHG	1.92204 ***	0.774429 ***	2.64741 ***	0.84501 ***
Jilin	Intercept	-0.0453625	0.047345	0.011519	-0.0155359
	RGRPPC	2.4633074 ***	-3.492099 *	1.221647 ***	0.9831274
	RGRPPC2	-0.3837647 ***	1.155241 ***	-0.461172 **	0.0934574
	RGRPPC3	0.0190355 ***	-0.067089 ***	0.032964 **	-0.0072636
	Pollutant/GHG	1.874508 ***	0.7698142 ***	2.634274 ***	0.8551879 ***
Liaoning	Intercept	-0.0592658	0.058457	0.024585	-0.021538
	RGRPPC	2.5079522 ***	-2.7363 .	1.264581 ***	-0.190763
	RGRPPC2	-0.3914401 ***	1.005003 ***	-0.486890 **	0.331368
	RGRPPC3	0.019367 ***	-0.059661 ***	0.034891 **	-0.01925
	Pollutant/GHG	1.871873 ***	0.776099 ***	2.63836 ***	0.857201 ***
Ningxia	Intercept	-0.02049168	-0.021671	0.072327	-0.00068067
	RGRPPC	0.57952911 ***	4.068797 .	1.583698 *	1.69565331
	RGRPPC2	-0.00909327	-0.410005	-0.673056 .	-0.09183536
	RGRPPC3	0.00047893	0.01354	0.04787	0.00388307
	Pollutant/GHG	1.86282 ***	0.775311 ***	2.653426 ***	0.86033917 ***
Qinghai	Intercept	-0.0246833	-0.018538	0.030276	0.022457
	RGRPPC	0.844907 ***	0.742308	1.474513 .	-2.30449
	RGRPPC2	-0.0650934 *	0.312783	-0.606145	0.651018
	RGRPPC3	0.0034393 *	-0.025192 *	0.043031	-0.030527

	Pollutant/GHG	1.847957 ***	0.7515117 ***	2.574306 ***	0.8640899 ***
Shaanxi	Intercept	-0.0106558	-0.064614	0.0802768	0.071409
	RGRPPC	0.316301	4.600339 **	0.3383116	1.994335
	RGRPPC2	0.0370996	-0.491452	0.0158644	-0.134022
	RGRPPC3	-0.0016193	0.016513	-0.0018361	0.004926
	Pollutant/GHG	1.896292 ***	0.829443 ***	2.750916 ***	0.892233 ***
Shandong	Intercept	-0.067034	-0.02192138	0.029891	-0.0056568
	RGRPPC	2.4207275 ***	-0.00084127	0.799273 **	-7.8644946
	RGRPPC2	-0.3644319 **	0.48001199	-0.226516	1.8450197 .
	RGRPPC3	0.0175093 **	-0.03438528 *	0.015238	-0.0936819 .
	Pollutant/GHG	1.896148 ***	0.770935 ***	2.63273 ***	0.8586455 ***
Shanghai	Intercept	-0.0432131	-0.083762	0.01306	-0.082863
	RGRPPC	1.2384015 .	4.932057 **	-0.227335	8.492761 **
	RGRPPC2	-0.1177607	-0.507514	0.35361 .	-1.275650 *
	RGRPPC3	0.0046056	0.014974	-0.028881 .	0.054746 *
	Pollutant/GHG	1.968149 ***	0.7649626 ***	2.621732 ***	0.862316 ***
Shanxi	Intercept	-0.1097311 *	0.031224	0.075742	0.015448
	RGRPPC	1.3918599 ***	0.93963	1.204622 **	-1.902575
	RGRPPC2	-0.1660277 *	0.250163	-0.459022 *	0.634756
	RGRPPC3	0.0081801 *	-0.021062	0.032295 *	-0.03263
	Pollutant/GHG	1.807892 ***	0.791815 ***	2.685633 ***	0.863401 ***
Sichuan	Intercept	-0.03846951	-0.0241805	-0.0155871	0.0046005
	RGRPPC	0.47043359 *	3.1094576 *	0.3727057	2.070144
	RGRPPC2	0.00728718	-0.162396	0.0186424	-0.1331989
	RGRPPC3	-0.00010946	-0.0014537	-0.0029263	0.0042731
	Pollutant/GHG	1.87855 ***	0.745815	2.556201 ***	0.8743737 ***
Tianjin	Intercept	-0.0942553 .	0.050573	0.054446	-0.026685
	RGRPPC	2.0522894 ***	-1.470959	1.186511 ***	-6.175154
	RGRPPC2	-0.2981725 ***	0.756604 *	-0.446142 **	1.496701
	RGRPPC3	0.0146863 ***	-0.047483 **	0.031641 *	-0.075779
	Pollutant/GHG	1.845916 ***	0.782964 ***	2.647315 ***	0.854754 ***
Xinjiang	Intercept	-0.0088677	-0.026423	0.012668	0.015745
	RGRPPC	0.9304116 ***	-0.421037	1.257436	-0.173972
	RGRPPC2	-0.0810943	0.529324	-0.482855	0.253209
	RGRPPC3	0.0041973	-0.035092 .	0.033707	-0.012014
	Pollutant/GHG	1.84549 ***	0.743308 ***	2.559891 ***	0.8637188 ***
Yunnan	Intercept	-0.0525167	0.00083909	-0.01712	0.0220434
	RGRPPC	0.3512357	3.61432221 **	0.938217 ***	2.016261
	RGRPPC2	0.02615367	-0.25517493	-0.297294 *	-0.1653072
	RGRPPC3	-0.00083735	0.00268101	0.020833 .	0.0077646
	Pollutant/GHG	1.886405 ***	0.76751 ***	2.5959730 ***	0.8747558 ***
Zhejiang	Intercept	-0.0647411	-0.081566	0.030437	-0.127645
	RGRPPC	0.5537402	6.336343 ***	-0.658634	8.844718 ***

RGRPPC2	0.0184078	-0.798056 *	0.596526 *	-1.334302 **
RGRPPC3	-0.0021064	0.029885	-0.04778 *	0.057199 *
Pollutant/GHG	1.9558 ***	0.7669134 ***	2.629365 ***	0.8546654 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The regions that showed highest correlation between economic development and CO2 emissions are generally located in the northern and northern-east China, which is the main industrialized area of the country (Beijing, Hebei, Helionjiang, Inner Mongolia, Jilin, Liaoning Shandong, Shanxi, Tianjin, Jiangsu, and Shanghai). None of these regions show evidences for the existence of the EKC with respect to CO_2 emissions, in most of the cases a N-shaped relationship reveals a negative effect of the economic development on environmental quality (fig. 1). This could mean that despite strong CO_2 emissions growth reductions registered in the recent years, these regions are struggling to maintain a sustained economic growth. Data show evidences for the existence of the EKC in only two regions, namely Jianxi and Hubei. However, in these regions, sustainable development seems to be only apparent. The turning points, which are expected to be respectively at the levels of 98 $x10^5$ million Yuan and 268 $x10^5$ million Yuan, are difficultly reachable given the levels of economic development in 2016 (39.5 $x10^5$ million Yuan in Jianxi and 54 $x10^5$ million Yuan in Hubei). These evidences suggest that in the next decades, the reduction of CO_2 emissions will require, ceteris paribus, a decrease in the per capita Gross Regional Product.

The regions which have the highest levels of Capital-Labor ratio, Qinghai, Ningxia, Inner Mongolia, Hebei and Shanxi are more likely to reveal a strong correlation between CO_2 emissions and the economic development. This could mean that a composition effect could be present, making the capital-intensive regions more likely to have high levels of economic development and consequent environmental degradation. Some of the regions which register the highest positive correlations between economic development and CO2 emissions such as Beijing, Jiangsu, Liaoning and Shandong, are in the set of the top regions in terms of Trade Openness and Foreign Direct Investments. The main insight could be that a certain amount of CO_2 emissions is potentially due to the strong commercial activities, which could suggest that the Heaven Pollution theory is potentially valid in the Chinese case. In order to confirm the theory, however, a deeper integrative research on the relationship between developed countries emission reduction, and Chinese CO_2

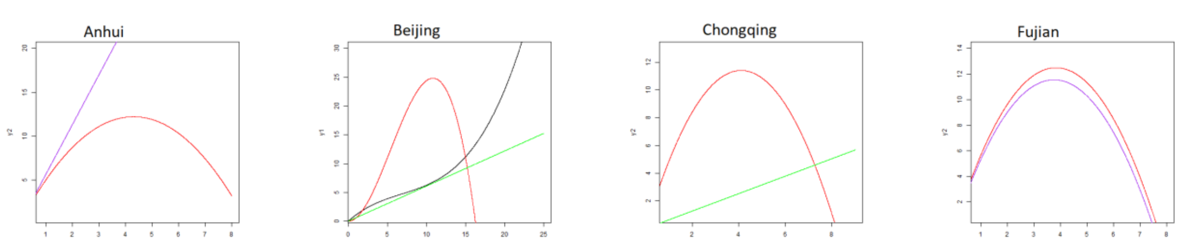
emission levels due to trade and FDI, would be necessary.

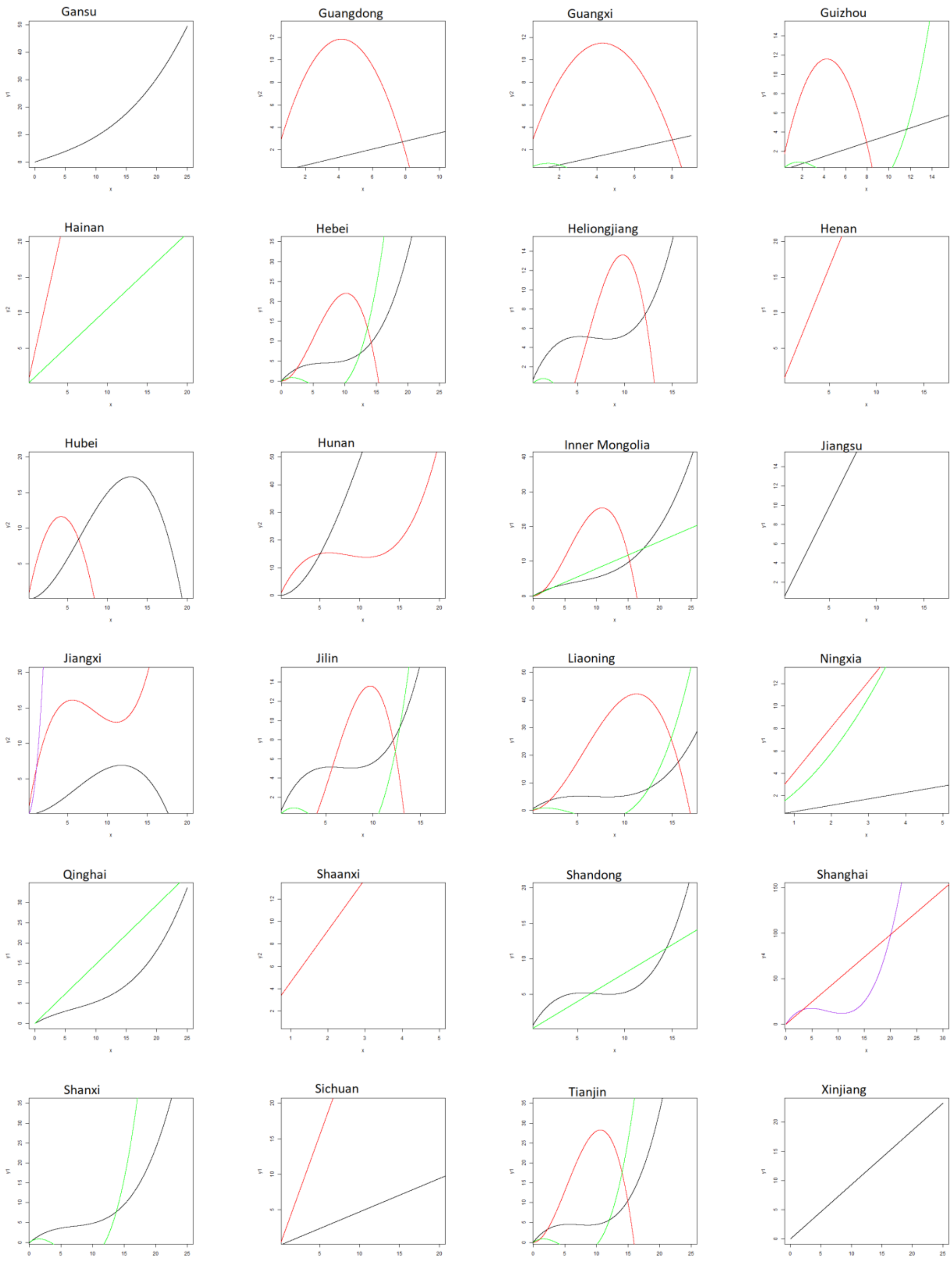
Analyzing the effect of CO2 on the economic development, the increase in a unit of emissions averagely cause the increase in 1.88 units of GDP. This result shows that eventual economic losses due to pollution, are strongly balanced and covered by the positive effects.

As regards SO_2, evidence in support of the EKC theory is showed. In fact, at a 1% level of significance, almost 27% of the individuals show a positive effect of the economic development on the environment. Into this set, accounting for almost 26% of total SO_2 emissions and 29% of the total analyzed area. However, at a 5% level of significance, the EKC theory is supported by 50% of the individuals, which account for almost 46% of total SO_2 emissions and 41% of the total analyzed area. To this extent it can be noticed that turning points have already been achieved for most of them. In the period between 2005 and 2010 Beijing, Helionjiang, Inner Mongolia, Jilin and Tianjing, inverted the trend, while Hebei reached the peak of the EKC in 2012-2013. Liaoning is expected to reach the turning point in the future, at a level of 71 x 10^5 million Yuan per capita (which seems to be achievable, considering the level of 49 x 10^5 million Yuan per capita registered in 2016). As regards Anhui, Chongqing, Fujian, Guangdong, Guangxi, Guizhou, Hubei and Zheijiang, the turning points have been reached in the period before the one analyzed. Analyzing the effects of SO_2 on the economic development, the increase in a unit of emissions averagely cause the increase in 0.76 units of GDP.

The analysis regarding PM2.5 concentrations as far it revealed low levels of significance for almost 50% of provinces (similarly to Stern and Zha in 2016), while the rest of the individuals showed a negative effect on the economic development, hence rejecting the EKC theory.

Finally, the analysis regarding WW discharges is straightforward as far as it showed low levels of significance, which means that no considerations could be moved in order to decide for the existence of the EKC in that case.




Gansu
Guangdong
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Hainan
Hebei
Heliongjiang
Henan
Hubei
Hunan
Inner Mongolia
Jiangsu
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Jilin
Liaoning
Ningxia
Qinghai
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Sichuan
Tianjin
Xinjiang

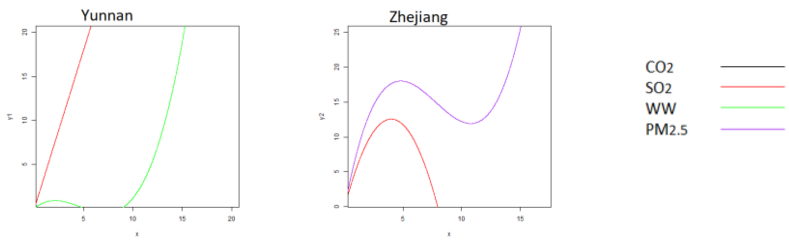


Fig.5 Shows the results of the analysis, pointing out the curves of the relationship between RGRPPC and the main pollutants/GHGs.

Conclusions

In this research the relationship between the economic development and environmental quality has been analyzed at a regional level in China. A new cross-regional panel data technique has been introduced in this specific literature for four pollutants/GHGs, for the first time, by mixing and taking inspiration from the Geographically Weighted Panel Data Regression - GWPR (provided by Yu et al, 2010) and the Error Component Three-Stages Least Squares model (provided by Baltagi, 2005). The question advanced at the beginning wondered if the classical Environmental Kuznets Curve theory was supposed to fit the Chinese economic development path. Consistently with other researches (e.g. Auffhammer et al. 2006), the estimated results point out that such a relationship does not empirically exist, hence rejecting the EKC theory.

As regards CO_2 emissions, the main trends reveal the existence of positive monotonic relationships and N-Shaped curves. Regarding SO2 emissions, some evidences of inverted U-Shaped curves have been showed, but their global impact at a national level is not enough to accept the theory at a 1% level of significance. Finally, no acceptable results have been provided by the analysis on PM2.5 and waste-water. The shape of the relationship heavily depends on the pollutants and on the province taken into consideration.

The philosophy “Pollute first and clean up later” has led China towards a complicated environmental situation, which does not show signals of natural recovery. For this reason, a public intervention is supposed to be necessary in the next decades. In order to face the issue, China should learn lessons from advanced countries, which already passed through this phase of development and gained experience in environmental management. By taking advantage by its “later comer” position, China could apply the “tunneling” technique to the EKC, by making more efforts on the introduction of newer and cleaner technologies, already introduced in other developed countries. Moreover, the increase in digitalization could be a source of clean development as well, as more economic value could be generated by services rather than industry. Another important phenomenon to be considered in the future is the impact that the carbon emission market, established at a national level in 2017. This could bring to the efficient allocation of emission credits, which would eventually be evident in the next years. Finally, China should continue its efforts on the decarbonization of its energy structure.

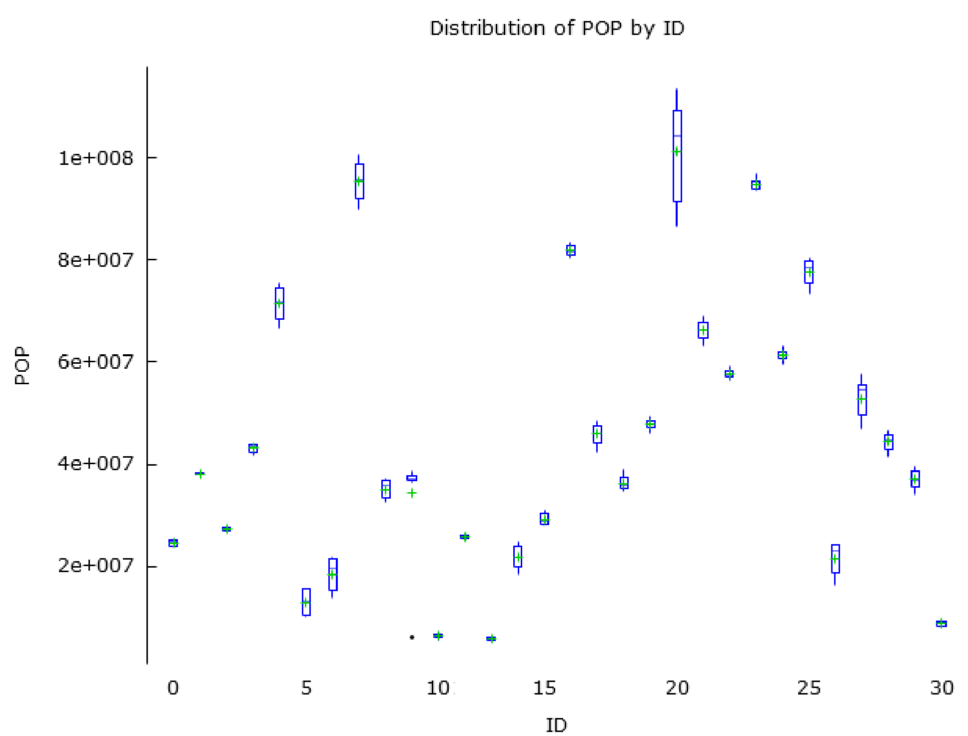
One of the main insights of this research is that, according to Y. Kim et al. (2017), regional policies which take into consideration the heterogeneity of provinces should be introduced in order to manage the specific characteristics of each individual. The local governments in central and western China should shift from the old development model of "get rich first and clean up later" to a more advanced sustainable development. In this regard, some pollution intensive industries in the last decades moved from east to west, in order to escape stringent environmental regulations. Moreover, in order to boost economic growth, some central and western provinces decided to attract these high-polluting enterprises, through special regulations, damaging the local environment. Nowadays, southeastern and central China are less polluted, while northeastern and western China register a bad environmental condition.

In conclusion, most provinces in China don't show success in the EKC theory, which suggests that the provincial governments cannot rely only on GDP in order to pursue a real sustainable development.

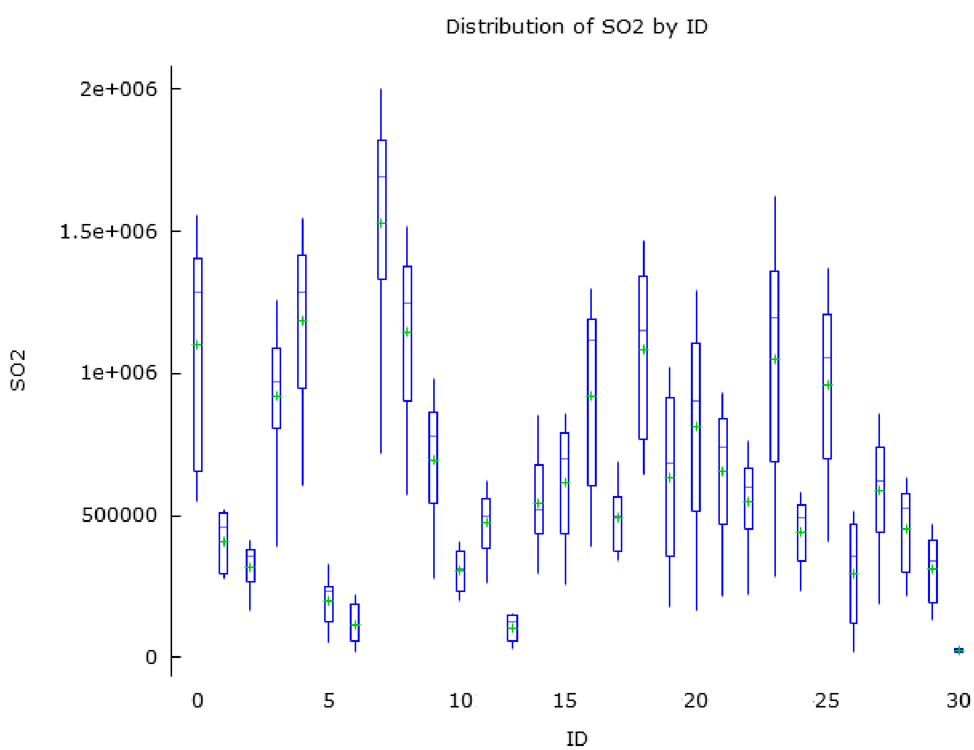
Appendix I - Descriptive statistics of data

In this appendix, cross-sectional descriptive statistics are provided for each variable at a provincial level.

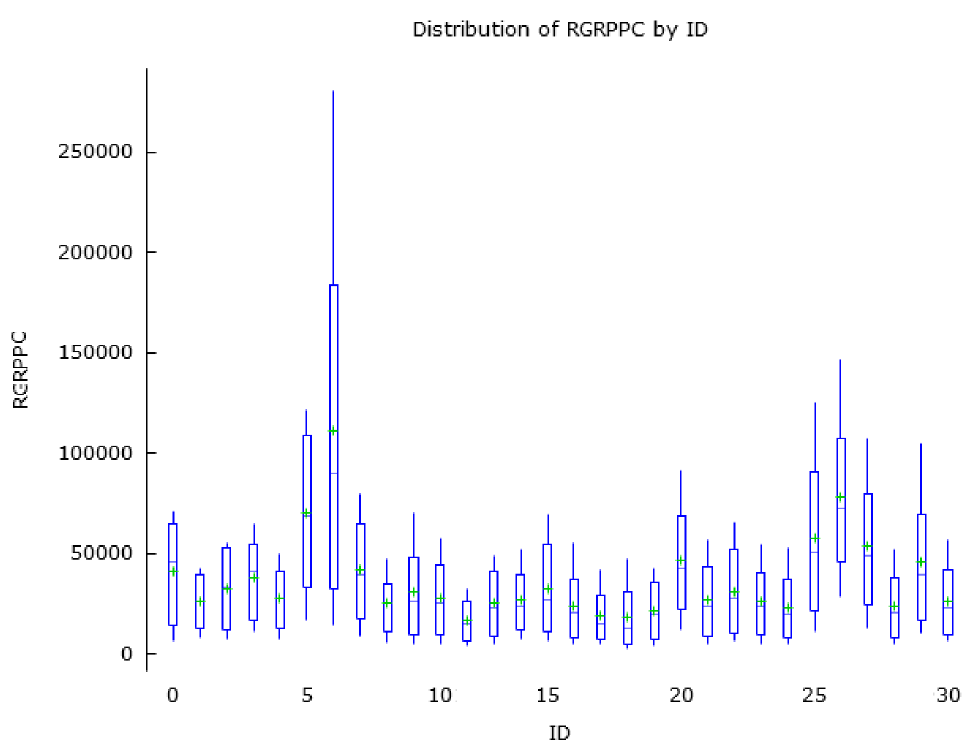
	Population (10000)													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	6122	6128	6144	94	87792515	0	0	5957	6088	6128	6154	6324	66
2	Beijing	1819	1860	2171	312	971089240	-2	0	1364	1516	1860	2134	2173	618
3	Chongqing	2903	2859		103	105470292	-1	1	2793	2815	2859	2981	3102	166
4	Fujian	3670	3666		161	260235848	-1	0	3410	3543	3666	3790	3941	247
5	Gansu	2565	2555		34	11890058	0	1	2515	2543	2555	2587	2637	44
6	Guangdong	9994	10130		894	7987264737	-1	0	8650	9153	10130	10684	11346	1532
7	Guangxi	4778	4788	4719	89	79346082	-1	0	4610	4719	4788	4847	4926	128
8	Guizhou	3635	3596		142	201830234	-1	1	3469	3519	3596	3743	3904	224
9	Hainan	861	864		46	21252865	-1	0	789	823	864	899	934	76
10	Hebei	7095	7034		302	910741345	-2	0	6674	6830	7034	7359	7556	529
11	Heilongjiang	3817	3820	3833	16	2710000	2	-1	3773	3812	3820	3830	3835	18
12	Henan	9490	9480		105	109960994	0	1	9360	9406	9480	9557	9717	152
13	Hubei	5754	5720		85	72006550	-1	1	5646	5696	5720	5808	5917	112
14	Hunan	6608	6629	6596	178	317548772	-1	0	6326	6484	6629	6718	6899	234
15	Inner Mongolia	2453	2458		56	31506082	-2	0	2372	2398	2458	2502	2534	104
16	Jiangsu	7750	7810		242	585051754	-1	-1	7327	7556	7810	7950	8051	394
17	Jiangxi	4415	4432		152	231747836	-1	0	4149	4298	4432	4532	4648	235
18	Jilin	2725	2730	2704	23	5129298	-1	0	2682	2707	2730	2748	2753	42
19	Liaoning	4309	4341		80	63570526	-2	0	4184	4219	4341	4380	4391	161
20	Ningxia	624	625		42	17305439	-1	0	554	592	625	658	688	66
21	Qinghai	560	557		26	6721404	-1	0	517	541	557	581	603	40
22	Shaanxi	3733	3727		63	39150994	0	1	3644	3686	3727	3770	3864	84
23	Shandong	9501	9470		340	1155496959	-1	0	8998	9214	9470	9761	10047	547
24	Shanghai	2127	2210	2415	300	898438713	-1	0	1609	1863	2210	2415	2426	553
25	Shanxi	3487	3427		165	273208129	-2	0	3247	3345	3427	3639	3718	294
26	Sichuan	8169	8143		88	78274269	0	1	8045	8109	8143	8208	8341	100
27	Tianjin	1261	1228		226	511909123	-2	0	1001	1034	1228	1495	1562	461
28	Xinjiang	2150	2159		196	385048304	-1	0	1849	1987	2159	2281	2487	295
29	Yunnan	4561	4571		178	315737076	-1	0	4241	4433	4571	4701	4830	268
30	Zhejiang	5242	5276		338	1141861520	-1	0	4680	4958	5276	5503	5737	545



	SO2 (100)													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	4609	4930	3960	1105	122138294	0	-1	2320	3960	4930	5352	5840	1392
2	Beijing	1254	1188		629	39535556	-1	0	201	830	1188	1864	2240	1034
3	Chongqing	6404	7194		1946	378737136	0	-1	2534	5373	7194	7885	8600	2512
4	Fujian	3244	3560		1106	122358701	-1	0	1339	2125	3560	4144	4690	2019
5	Gansu	4778	5020		1105	122195514	0	-1	2588	3985	5020	5625	6239	1640
6	Guangdong	8822	9730		3205	1027214216	0	-1	2173	7460	9730	11056	12940	3596
7	Guangxi	6686	6970		2895	838212750	-1	0	1773	4693	6970	9144	10240	4451
8	Guizhou	11295	11755		2695	726260526	-1	-1	6471	9561	11755	13415	14650	3854
9	Hainan	249	230	220	57	329603	-1	0	143	220	230	306	341	86
10	Hebei	12343	12890		2756	759748702	1	-1	6024	12118	12890	14171	15450	2053
11	Heilongjiang	4210	4722		970	94161065	-2	0	2806	3174	4722	5070	5219	1896
12	Henan	11159	12540	16240	4130	1705895445	0	-1	2863	9170	12540	13628	16240	4458
13	Hubei	5727	6086		1518	230413191	1	-1	2201	5457	6086	6678	7600	1221
14	Hunan	6947	7620		2169	470355016	1	-1	2146	6325	7620	8442	9340	2117
15	Inner Mongolia	11386	13124		3665	1343172514	-1	-1	5463	6974	13124	14041	15570	7067
16	Jiangsu	10113	10742		2809	789150582	1	-1	4070	9232	10742	12099	13730	2867
17	Jiangxi	4705	5344		1458	212441685	-1	-1	2155	3146	5344	5753	6340	2608
18	Jilin	3235	3629	2650	800	63969325	-1	-1	1661	2685	3629	3822	4132	1138
19	Liaoning	9319	9946		2463	606539250	0	-1	3897	8269	9946	10924	12590	2655
20	Ningxia	3105	3142		734	53910670	-1	0	2000	2347	3142	3734	4104	1387
21	Qinghai	1099	1300	320	451	20359996	-1	-1	320	740	1300	1471	1567	731
22	Shaanxi	7240	7810		2132	454668442	0	-1	2794	6307	7810	8664	9810	2357
23	Shandong	16001	16920		3602	1297124278	2	-2	7194	15640	16920	18216	20020	2575
24	Shanghai	3245	3789		1721	296339011	-1	-1	184	2020	3789	4690	5130	2670
25	Shanxi	11970	12554	11990	2751	756652457	1	-1	5731	11990	12554	13751	15160	1761
26	Sichuan	9734	11310		2997	898208535	0	-1	3891	8066	11310	11927	13000	3861
27	Tianjin	2127	2350		741	54968240	1	-1	520	2130	2350	2499	3299	368
28	Xinjiang	5526	5490		1830	334973631	-1	0	2960	4345	5490	6765	8530	2420
29	Yunnan	5080	5020		1088	118458754	-1	0	3485	4192	5020	5674	6912	1481
30	Zhejiang	6164	6258		1926	370832967	1	-1	1905	5830	6258	7377	8600	1546

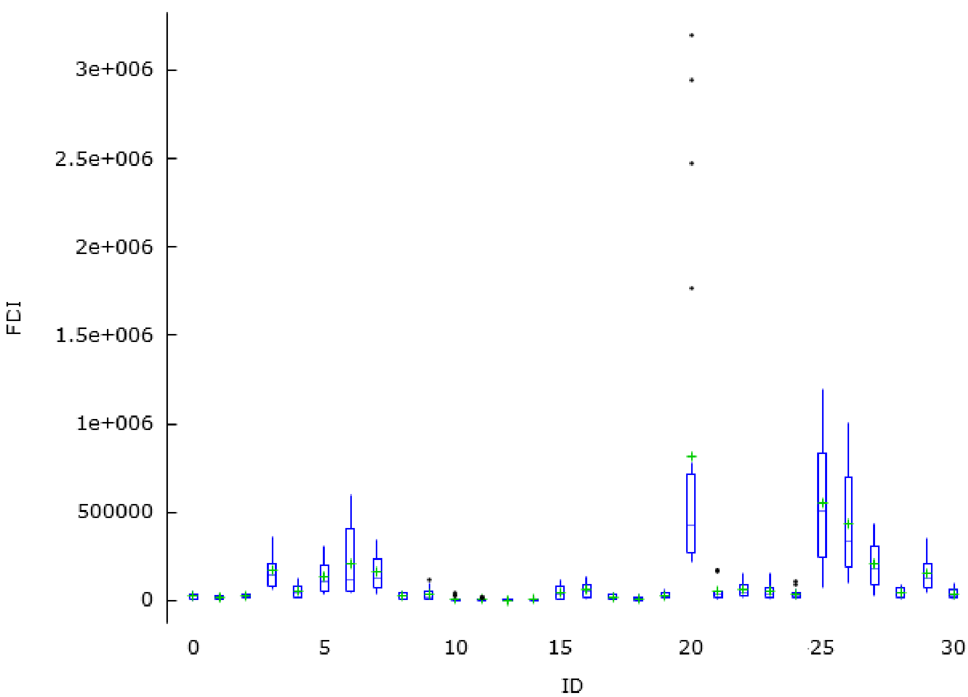


	RGRPPC													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	20431	16543		13922	193817190	-1	1	4958	8038	16543	30989	46595	22951
2	Beijing	94905	76950		72642	5276932448	-1	1	14213	32348	76950	142326	238868	109979
3	Chongqing	28820	23164		20085	403418961	-1	1	6479	11417	23164	44460	64393	33043
4	Fujian	40130	35421		25483	649364595	-1	1	10822	16939	35421	59206	89625	42268
5	Gansu	15430	13097		9290	86311290	-2	0	4205	7002	13097	24636	30705	17633
6	Guangdong	42227	39811		23013	529605456	-1	0	12281	22123	39811	59481	83998	37357
7	Guangxi	19468	16282		12849	165088678	-2	0	4390	7571	16282	31097	40452	23526
8	Guizhou	15392	11193		12512	156558070	-1	1	2754	4741	11193	24121	40452	19379
9	Hainan	23528	19268		14925	222751771	-1	0	6611	10047	19268	36097	50541	26050
10	Hebei	25692	24662		13654	186426201	-2	0	7578	13202	24662	38350	46577	25148
11	Heilongjiang	24822	22400		12690	161048033	-2	0	8406	13163	22400	37923	42522	24760
12	Henan	23035	20648		14620	213732219	-1	0	5364	9758	20648	34814	48965	25056
13	Hubei	28713	23230		19970	398810623	-1	0	6728	10298	23230	45641	65392	35342
14	Hunan	23939	20459		16118	259793848	-1	0	5341	9145	20459	37616	51816	28471
15	Inner Mongolia	39361	39730		25290	639569951	-2	0	6420	14183	39730	63889	71088	49706
16	Jiangsu	51097	44278		33257	1106000240	-1	0	11664	21680	44278	76544	112558	54864
17	Jiangxi	20837	17366		13795	190314023	-1	0	4764	8571	17366	30996	46396	22425
18	Jilin	30652	27953		18824	354358612	-2	0	7043	12205	27953	50756	55427	38551
19	Liaoning	36298	35044		19628	385245474	-2	0	11169	17084	35044	54030	64510	36947
20	Ningxia	24933	21518		16583	275007100	-1	0	5343	9499	21518	39420	52703	29922
21	Qinghai	22779	18937		14782	218512869	-2	0	5124	9177	18937	36786	46428	27610
22	Shaanxi	26821	21822		19137	366220159	-1	0	4971	9483	21822	43828	62056	34345
23	Shandong	38034	35794		22438	503443452	-1	0	9249	17737	35794	57350	74305	39613
24	Shanghai	71244	68338		31727	1006586275	-1	0	29026	45847	68338	91135	132796	45288
25	Shanxi	22859	21790		12790	163581481	-1	0	5448	11116	21790	34039	44483	22923
26	Sichuan	21129	17166		14367	206397809	-1	0	4712	8212	17166	33055	48015	24843
27	Tianjin	65250	61800		36078	1301609977	-2	0	17060	33400	61800	98390	118197	64990
28	Xinjiang	24045	19675		13745	188928357	-1	0	7413	11937	19675	37455	48176	25518
29	Yunnan	16549	13448		10626	112911416	-1	1	4834	7159	13448	25456	36478	18298
30	Zhejiang	48117	44186		26879	722468316	-1	0	13007	24732	44186	69192	95880	44460

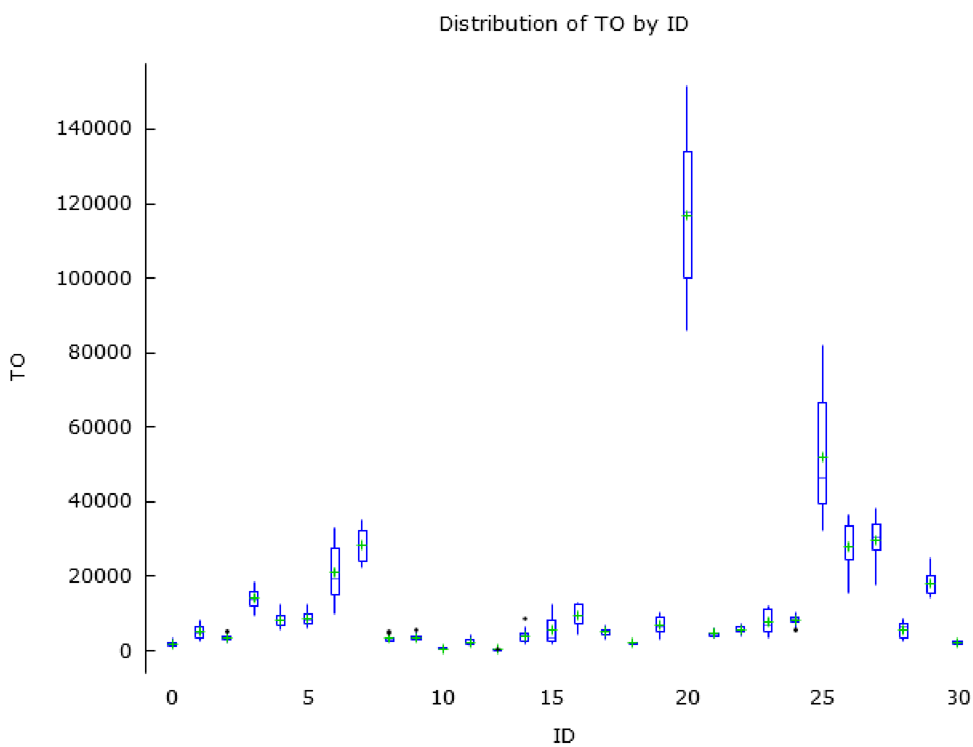


	FDI (10)													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	3397	2790		2691	72435625	2	2	914	1421	2790	4079	10649	2658
2	Beijing	17120	10660		15954	2545402471	0	1	4025	5692	10660	18907	52589	13215
3	Chongqing	3931	2780		3357	112665706	-1	1	655	764	2780	6318	10218	5554
4	Fujian	13181	11750		7180	515578284	0	1	4708	7210	11750	16488	29519	9278
5	Gansu	626	490		532	2830390	4	2	216	293	490	687	2038	394
6	Guangdong	57845	39390		57648	33233068533	7	3	21651	27494	39390	53735	247800	26241
7	Guangxi	2754	2720		1523	23204583	0	1	1025	1369	2720	3466	6010	2097
8	Guizhou	934	360		1061	11267079	1	1	149	229	360	1366	3559	1138
9	Hainan	3908	2699		3143	98762892	-1	1	863	1665	2699	6548	9666	4883
10	Hebei	4426	3700		2856	81593369	0	1	1401	2099	3700	5834	10648	3735
11	Heilongjiang	1804	1810		847	7170000	-1	0	747	1022	1810	2255	3436	1233
12	Henan	4229	3470		3207	102875983	1	1	1007	1775	3470	5333	12051	3558
13	Hubei	5120	3770		3556	126486041	0	1	1414	2424	3770	7151	12927	4728
14	Hunan	4192	2800		4651	216302177	5	2	657	1386	2800	4340	16975	2953
15	Inner Mongolia	2163	2291		1462	21369412	0	0	222	1173	2291	2613	5221	1440
16	Jiangsu	48720	44440		30116	9069986848	-1	0	7500	24135	44440	69225	104661	45090
17	Jiangxi	4125	3690		2660	70768554	-1	0	688	1741	3690	6290	8476	4549
18	Jilin	2494	2325		948	8989919	-1	0	766	1878	2325	3255	3887	1377
19	Liaoning	14884	13180		8085	653664993	0	1	6380	7750	13180	19210	33273	11460
20	Ningxia	649	396		810	6559371	5	3	94	247	396	481	3042	234
21	Qinghai	314	280	70	254	646785	0	1	58	87	280	323	770	236
22	Shaanxi	2939	1647		2486	61807831	1	1	832	1308	1647	4068	9273	2760
23	Shandong	13955	11200		8870	786737142	0	1	3895	7402	11200	18786	34004	11384
24	Shanghai	37653	30840		24361	5934679894	0	1	9854	18643	30840	49420	89366	30777
25	Shanxi	2364	2050		1622	26323427	-1	0	483	731	2050	3665	5235	2934
26	Sichuan	5052	4610		3658	133793455	-1	1	1011	1529	4610	7762	12107	6233
27	Tianjin	11291	9770		7465	557214803	0	1	3309	5191	9770	13578	27952	8388
28	Xinjiang	528	480		403	1620673	0	1	112	165	480	712	1432	547
29	Yunnan	1820	1590		1131	12796638	-1	1	482	816	1590	2468	3978	1652
30	Zhejiang	18168	16400		11392	1297864273	-1	0	2931	9267	16400	25164	41377	15897

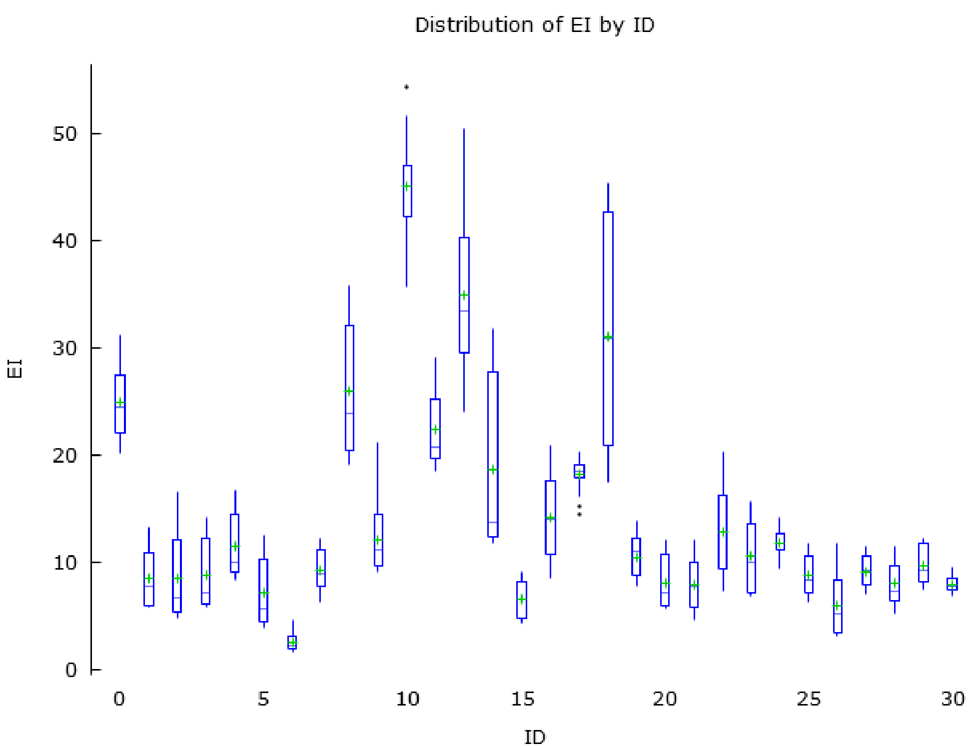
Distribution of FDI by ID



	TO													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	8242	8497		1494	2232674	0	0	5588	7682	8497	9020	10535	1339
2	Beijing	21947	22145		6959	48427337	-1	0	9909	16441	22145	27604	32877	11163
3	Chongqing	5220	3395		3277	10740007	-1	1	1864	2613	3395	7761	12534	5148
4	Fujian	18588	18472		3438	11817215	-1	0	14059	15791	18472	20413	24950	4622
5	Gansu	2326	2057		889	790192	-1	0	1121	1583	2057	2953	4140	1370
6	Guangdong	118582	118342		21309	454081958	-1	0	85845	105080	118342	133943	151575	28863
7	Guangxi	6421	6068		2097	4396172	0	1	3142	5150	6068	7304	10479	2153
8	Guizhou	2023	2065		493	243510	0	0	1157	1701	2065	2286	3018	585
9	Hainan	2157	1986		485	235617	-1	1	1492	1794	1986	2570	3017	776
10	Hebei	8557	8964		1725	2975490	0	0	5723	7489	8964	9366	12299	1878
11	Heilongjiang	5166	4949		1755	3078940	-1	0	2752	3562	4949	6554	7968	2992
12	Henan	7615	6506		3037	9220606	-2	0	3523	5317	6506	11046	12024	5728
13	Hubei	5573	5425		996	992288	-1	0	3966	5034	5425	6433	7384	1399
14	Hunan	4531	4378		671	449830	0	0	3389	4033	4378	4942	6034	909
15	Inner Mongolia	1832	1571		674	453951	-1	1	1087	1224	1571	2367	3381	1143
16	Jiangsu	53436	51877		16807	282465433	-1	0	32391	39628	51877	66689	81838	27061
17	Jiangxi	5593	6263		2044	4176958	-1	0	2409	3652	6263	7182	8494	3531
18	Jilin	3421	3454		863	744927	1	1	2140	2945	3454	3782	5353	837
19	Liaoning	14008	13552		2700	7290570	-1	0	9344	12083	13552	16069	18587	3986
20	Ningxia	638	684		171	29222	-1	0	382	498	684	763	969	265
21	Qinghai	281	258		108	11749	2	1	101	230	258	322	566	92
22	Shaanxi	3504	3374		768	589365	3	2	2485	3040	3374	3618	5773	578
23	Shandong	28717	28609		4190	17558962	-1	0	22368	24822	28609	32128	35165	7305
24	Shanghai	28484	30334		6500	42256175	0	-1	15603	25629	30334	33713	36529	8085
25	Shanxi	3301	3091		766	586800	1	1	2656	2740	3091	3526	5157	786
26	Sichuan	9284	8906		2613	6826414	-1	0	4472	7411	8906	11492	12908	4081
27	Tianjin	8807	8324		1966	3864933	-1	1	6070	7504	8324	9906	12544	2402
28	Xinjiang	4272	4307		1551	2404641	2	1	1914	3048	4307	4914	8439	1866
29	Yunnan	5072	5455		1150	1321939	-1	0	3104	4205	5455	5826	6862	1621
30	Zhejiang	29738	30596		5910	34924135	0	-1	17714	27672	30596	33962	38322	6290

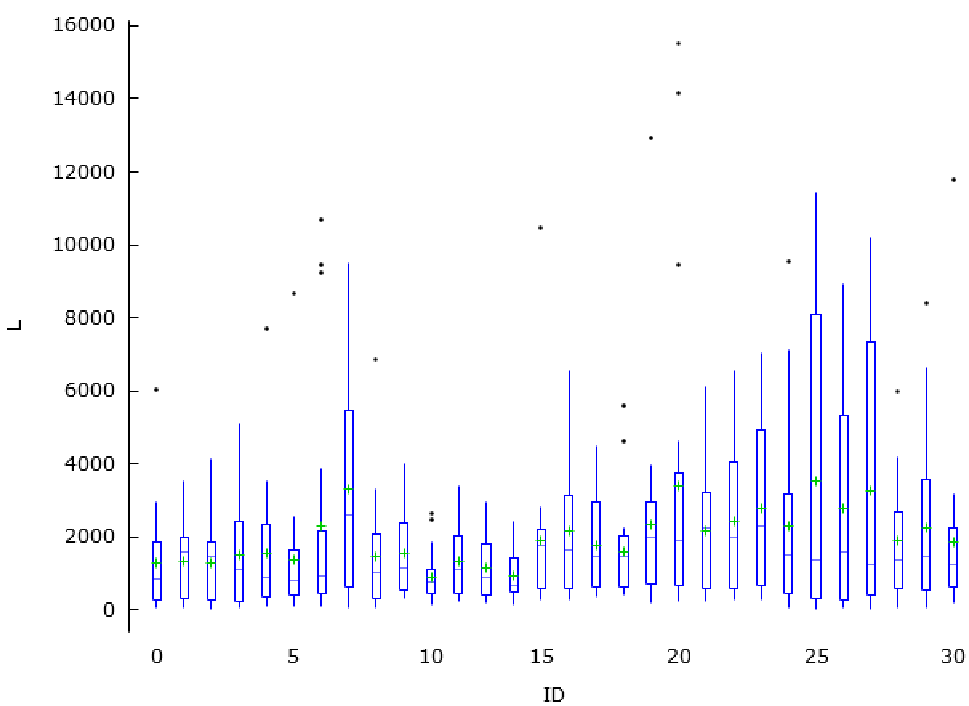


							EI							
	Province	*Mean*	*Median*	*Mode*	*St. Dev.*	*Variance*	*Kurt.*	*Skew*	*Min*	*1Q*	*2Q*	*3Q*	*Max*	*IQ Range*
1	*Anhui*	11.86	11.98		1.24	1.54	-0.30	-0.18	9.49	11.16	11.98	12.70	14.24	1.54
2	*Beijing*	2.54	2.17		0.88	0.77	0.38	1.10	1.68	1.91	2.17	3.17	4.71	1.27
3	*Chongqing*	6.73	7.16		1.76	3.10	-1.69	-0.07	4.38	4.82	7.16	8.26	9.15	3.44
4	*Fujian*	9.88	9.34		1.85	3.42	-1.76	0.07	7.43	8.20	9.34	11.76	12.34	3.57
5	*Gansu*	22.67	21.52		3.62	13.10	-1.24	0.51	18.51	19.67	21.52	25.27	29.21	5.60
6	*Guangdong*	8.34	7.49		2.44	5.95	-1.48	0.46	5.62	6.17	7.49	10.73	12.17	4.57
7	*Guangxi*	10.68	11.15		2.00	4.00	-1.55	-0.04	7.85	8.78	11.15	12.22	13.86	3.44
8	*Guizhou*	32.02	34.86		10.77	115.92	-1.82	-0.13	17.56	20.97	34.86	42.72	45.41	21.75
9	*Hainan*	7.95	7.69		0.80	0.64	-0.30	0.86	6.92	7.42	7.69	8.50	9.56	1.08
10	*Hebei*	11.70	10.04	16.70	3.16	9.98	-1.37	0.61	8.46	9.12	10.04	14.47	16.70	5.35
11	*Heilongjiang*	8.85	8.44	10.92	2.77	7.68	-1.51	0.31	5.85	6.04	8.44	10.92	13.33	4.89
12	*Henan*	11.03	10.49		3.08	9.49	-1.54	-0.01	6.87	8.52	10.49	13.62	15.65	5.11
13	*Hubei*	13.11	13.68	13.68	4.11	16.89	-1.02	0.24	7.34	9.44	13.68	16.32	20.34	6.89
14	*Hunan*	8.10	7.84	7.84	2.38	5.65	-1.34	0.09	4.61	5.86	7.84	10.04	12.05	4.19
15	*Inner Mongolia*	25.05	24.12		3.16	9.97	-1.18	0.24	20.19	22.16	24.12	27.52	31.18	5.36
16	*Jiangsu*	8.96	8.47		1.88	3.54	-1.65	0.05	6.32	7.27	8.47	10.65	11.82	3.38
17	*Jiangxi*	8.08	7.20		1.97	3.86	-1.33	0.33	5.26	6.38	7.20	9.66	11.48	3.28
18	*Jilin*	8.82	7.07		3.92	15.37	-0.76	0.75	4.79	5.45	7.07	12.18	16.60	6.73
19	*Liaoning*	9.09	7.64		3.26	10.62	-1.61	0.44	5.84	6.13	7.64	12.26	14.16	6.14
20	*Ningxia*	44.99	45.10		4.84	23.46	0.23	-0.14	35.68	42.33	45.10	47.01	54.38	4.68
21	*Qinghai*	35.18	34.03		7.57	57.32	-0.54	0.50	24.01	29.65	34.03	40.41	50.51	10.76
22	*Shaanxi*	12.38	11.35		3.26	10.61	1.51	1.24	9.09	9.74	11.35	14.56	21.29	4.83
23	*Shandong*	9.29	8.95		2.05	4.19	-1.51	0.08	6.32	7.74	8.95	11.22	12.21	3.49
24	*Shanghai*	6.33	5.25		2.94	8.66	-0.92	0.66	3.10	3.98	5.25	8.46	11.84	4.48
25	*Shanxi*	26.62	25.09		6.43	41.30	-1.68	0.27	19.21	20.93	25.09	32.14	35.89	11.21
26	*Sichuan*	13.52	12.75		3.35	11.21	-0.58	0.60	8.58	10.84	12.75	15.16	19.71	4.32
27	*Tianjin*	7.34	5.94		3.23	10.44	-1.30	0.60	3.83	4.58	5.94	10.35	12.52	5.77
28	*Xinjiang*	17.24	13.29	12.93	7.07	50.04	-0.41	1.13	11.86	12.38	13.29	21.83	31.34	9.45
29	*Yunnan*	18.30	18.71		1.59	2.52	0.78	-1.17	14.53	18.15	18.71	19.17	20.35	1.03
30	*Zhejiang*	9.31	9.57		1.48	2.20	-1.47	-0.06	7.11	7.94	9.57	10.61	11.53	2.67

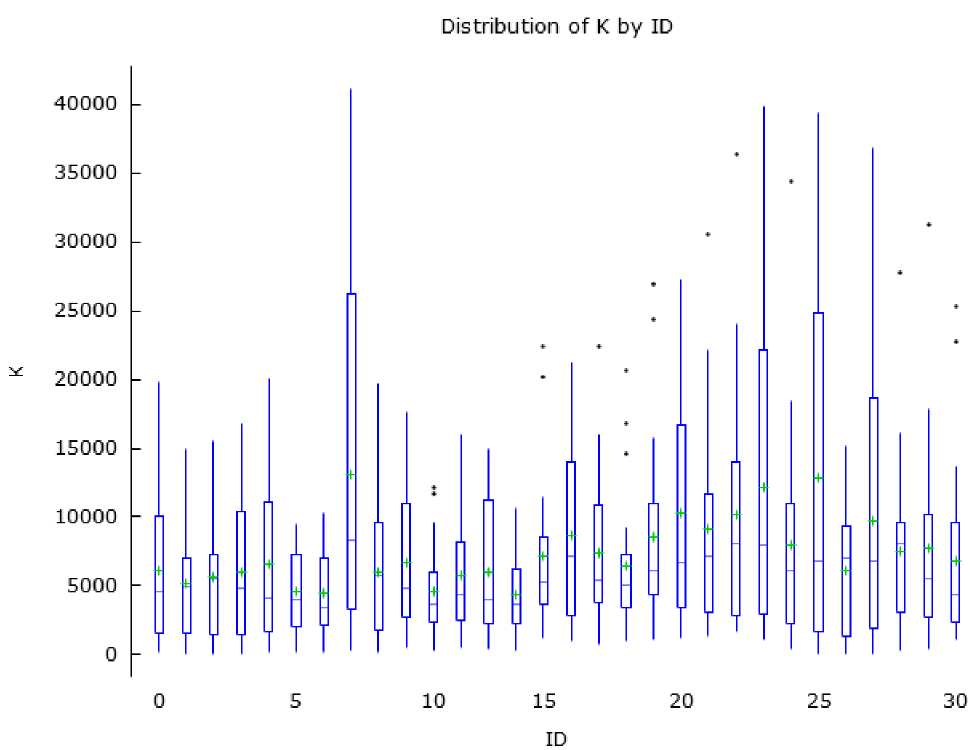


	Labour													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	2242	991		2629	6913970	2	2	63	459	991	3168	9552	2709
2	Beijing	2241	588		3420	11695319	2	2	115	457	588	1788	10676	1332
3	Chongqing	1896	1298		2244	5034171	13	3	278	591	1298	2200	10467	1610
4	Fujian	2230	1315		2386	5694421	1	1	61	533	1315	3572	8396	3039
5	Gansu	1273	950		971	943742	0	1	250	450	950	1767	3381	1317
6	Guangdong	3486	1602		4570	20883672	3	2	238	652	1602	3760	15512	3108
7	Guangxi	2277	1591		2825	7978643	12	3	211	720	1591	2906	12919	2186
8	Guizhou	1622	1282	422	1396	1949862	3	2	422	649	1282	2032	5575	1383
9	Hainan	1866	1185		2558	6541431	14	4	186	645	1185	2237	11765	1592
10	Hebei	1501	702		1849	3417151	6	2	91	364	702	2119	7688	1755
11	Heilongjiang	1294	1051		1100	1210219	-1	1	45	322	1051	2002	3546	1679
12	Henan	2570	2118		2172	4715820	-1	1	268	663	2118	3788	7055	3125
13	Hubei	2266	1878		1902	3619367	0	1	267	584	1878	3841	6545	3257
14	Hunan	2070	1632		1688	2847906	0	1	245	592	1632	3225	6099	2633
15	Inner Mongolia	1261	674		1446	2090619	6	2	70	260	674	1859	6012	1599
16	Jiangsu	2881	1287		3928	15429722	1	2	36	321	1287	2503	11433	2182
17	Jiangxi	1868	1278		1669	2786903	0	1	57	598	1278	2716	5985	2117
18	Jilin	1261	851		1181	1395889	0	1	21	270	851	1862	4136	1592
19	Liaoning	1406	712		1422	2022836	1	1	54	231	712	2378	5100	2147
20	Ningxia	918	721		730	533228	1	1	169	464	721	1127	2662	663
21	Qinghai	1103	802		878	770448	0	1	197	427	802	1641	2935	1214
22	Shaanxi	1469	1090		1211	1467182	0	1	306	524	1090	1870	4003	1346
23	Shandong	3106	2465		2884	8318970	0	1	64	619	2465	4493	9509	3875
24	Shanghai	2158	1305		2682	7194466	1	2	39	290	1305	2665	8259	2374
25	Shanxi	1405	773		1635	2672869	6	2	75	322	773	2098	6870	1776
26	Sichuan	1976	1601		1829	3345236	1	1	265	608	1601	2424	6561	1816
27	Tianjin	1390	811		1922	3694197	12	3	104	420	811	1621	8644	1201
28	Xinjiang	926	635		718	515395	0	1	129	481	635	1219	2409	739
29	Yunnan	1636	1265		1267	1606134	0	1	354	620	1265	2226	4484	1606
30	Zhejiang	2838	1107		3479	12105975	0	1	30	393	1107	4397	10194	4004

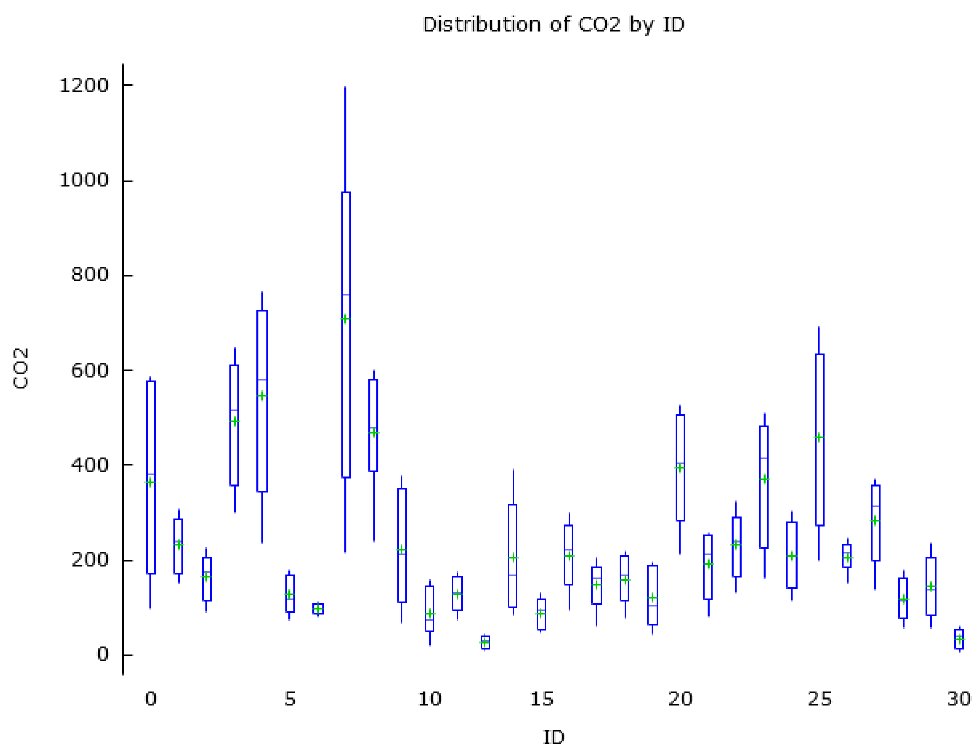
Distribution of L by ID



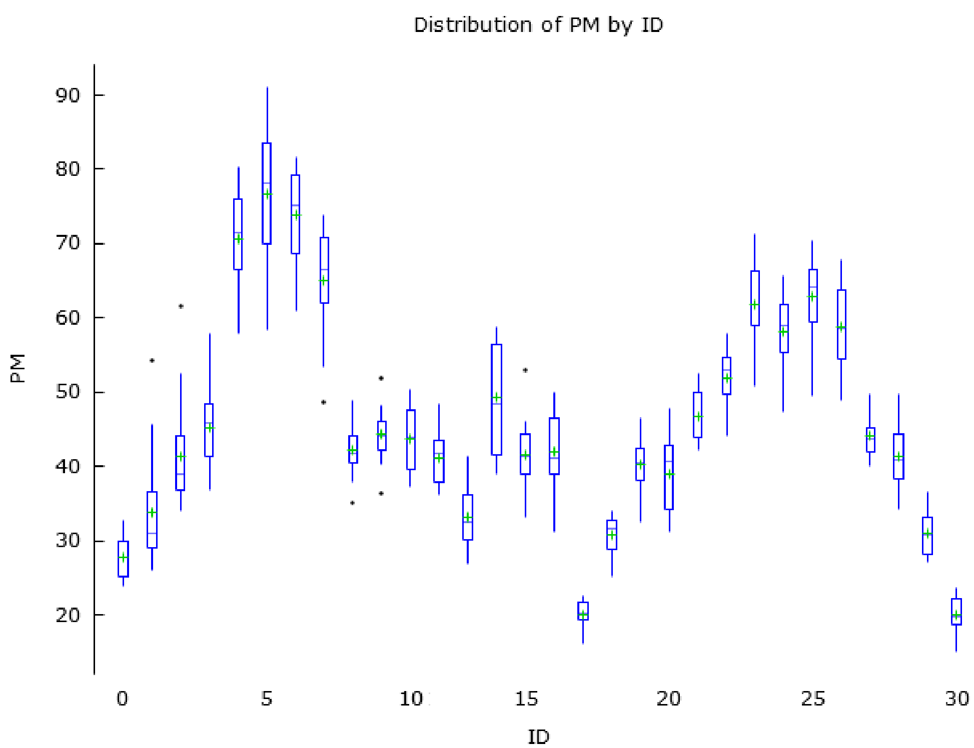
	Capital													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	7812	6063		8077	65232684	6	2	390	2268	6063	10988	34449	8720
2	Beijing	4567	3408		3158	9971536	-1	0	180	2159	3408	7046	10245	4887
3	Chongqing	7290	5587		5731	32846036	2	2	1222	3614	5587	8487	22386	4873
4	Fujian	7650	5520		7346	53961719	5	2	386	2761	5520	10231	31249	7470
5	Gansu	5525	4327		4605	21207131	1	1	467	2442	4327	7618	16002	5176
6	Guangdong	10805	6710		9013	81240092	-1	1	1154	3570	6710	16641	27313	13071
7	Guangxi	8554	6071		7195	51761537	2	2	1095	4295	6071	10991	26944	6696
8	Guizhou	6645	5396		5309	28188519	2	2	924	3407	5396	7298	20665	3891
9	Hainan	7224	4489		6967	48539552	2	2	1064	2376	4489	9570	25305	7194
10	Hebei	5755	3446		5923	35077836	1	1	141	1646	3446	7643	20088	5996
11	Heilongjiang	5232	4969		4366	19059908	0	1	69	1532	4969	7059	14954	5527
12	Henan	11110	6872		11002	121053385	1	1	1146	2898	6872	18411	39914	15514
13	Hubei	9777	7124		9133	83410191	3	2	1701	2842	7124	13172	36420	10330
14	Hunan	9089	7072		7808	60962801	2	1	1339	3044	7072	11721	30513	8678
15	Inner Mongolia	5694	3104		5592	31266864	1	1	104	1565	3104	9358	19804	7793
16	Jiangsu	10158	6739		13015	169401795	2	2	54	1625	6739	9301	39401	7676
17	Jiangxi	7252	5300		6475	41924669	5	2	316	3059	5300	9495	27740	6436
18	Jilin	5474	4429		4821	23237726	0	1	75	1404	4429	7232	15564	5828
19	Liaoning	5680	3755		5237	27422723	-1	1	76	1420	3755	10411	16765	8990
20	Ningxia	4374	3411		3462	11984362	1	1	268	2314	3411	5646	12134	3333
21	Qinghai	5207	3661		4340	18831336	0	1	341	2272	3661	6664	13644	4392
22	Shaanxi	6310	4653		5111	26124876	0	1	530	2736	4653	9147	17654	6412
23	Shandong	11430	7141		12630	159505748	1	1	319	3322	7141	13034	41145	9712
24	Shanghai	5538	4971		4351	18932462	-1	0	54	1267	4971	8599	15138	7331
25	Shanxi	5645	3563		5243	27488545	1	1	131	1759	3563	7781	19746	6022
26	Sichuan	8025	6617		6178	38171621	0	1	995	2813	6617	10296	21209	7483
27	Tianjin	4273	3711		2954	8725242	-1	0	174	1971	3711	6612	9421	4642
28	Xinjiang	4297	3607		3045	9270580	0	1	244	2199	3607	5277	10624	3078
29	Yunnan	6909	5156		5368	28817786	3	2	720	3782	5156	8555	22408	4773
30	Zhejiang	8689	6532		9471	89694230	3	2	53	1884	6532	10372	36791	8488



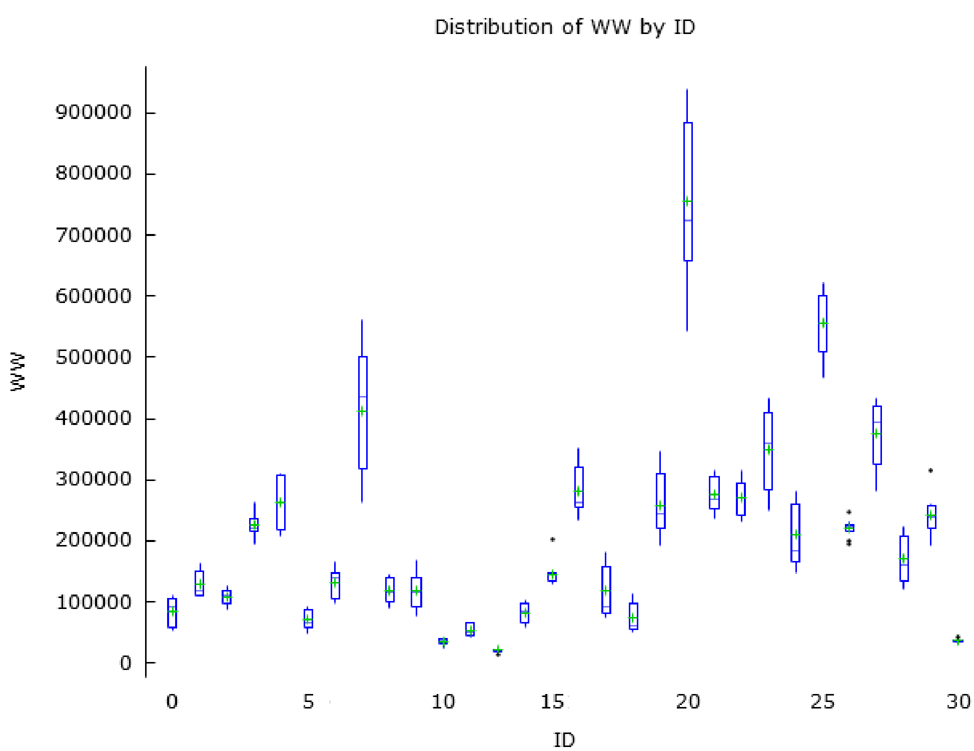
	CO2													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	209	208		71	4986	-2	0	115	145	208	270	304	125
2	Beijing	97	98		10	108	-1	0	80	88	98	105	113	17
3	Chongqing	88	96		31	941	-2	0	47	54	96	116	130	62
4	Fujian	146	138		64	4090	-2	0	55	90	138	207	235	117
5	Gansu	129	130		36	1328	-1	0	74	100	130	164	174	64
6	Guangdong	395	405		115	13203	-1	0	211	300	405	505	527	205
7	Guangxi	120	104		59	3502	-2	0	44	73	104	186	195	114
8	Guizhou	158	169		50	2455	-1	0	78	123	169	208	221	86
9	Hainan	34	40		20	408	-2	0	7	12	40	51	61	39
10	Hebei	547	581		195	37837	-1	0	236	373	581	726	765	354
11	Heilongjiang	233	238		56	3172	-2	0	151	180	238	287	306	107
12	Henan	369	417		128	16298	-1	-1	161	268	417	481	510	213
13	Hubei	234	239		67	4430	-1	0	133	174	239	288	324	114
14	Hunan	192	211		66	4298	-1	-1	81	132	211	249	256	117
15	Inner Mongolia	365	380		191	36545	-2	0	98	190	380	571	586	381
16	Jiangsu	457	457		177	31278	-1	0	197	301	457	628	693	327
17	Jiangxi	119	114		43	1845	-1	0	56	86	114	155	179	69
18	Jilin	165	174		47	2163	-1	0	91	119	174	197	226	78
19	Liaoning	492	517		126	15885	-1	0	300	373	517	608	647	235
20	Ningxia	89	75		48	2323	-2	0	20	51	75	139	157	88
21	Qinghai	27	30		13	157	-2	0	11	15	30	39	45	24
22	Shaanxi	222	211		114	13070	-2	0	67	122	211	341	376	218
23	Shandong	708	760		321	103135	-1	0	215	420	760	963	1197	543
24	Shanghai	207	215		31	954	-1	-1	150	189	215	233	246	45
25	Shanxi	468	479		113	12745	0	-1	238	395	479	576	599	181
26	Sichuan	207	222		72	5129	-1	0	93	159	222	272	299	113
27	Tianjin	127	119		38	1445	-2	0	73	97	119	165	177	68
28	Xinjiang	204	170		110	12182	-1	1	83	106	170	297	391	191
29	Yunnan	148	162		49	2363	-1	-1	59	121	162	182	206	61
30	Zhejiang	283	315		86	7396	-1	-1	137	214	315	354	371	140



	PM 2.5													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	58	59		5	22	1	-1	47	56	59	62	66	6
2	Beijing	74	75		6	38	-1	-1	61	70	75	78	82	9
3	Chongqing	42	41		5	20	2	1	33	39	41	43	53	4
4	Fujian	31	31		3	9	-1	0	27	28	31	33	37	4
5	Gansu	41	42		3	10	0	0	36	38	42	43	48	5
6	Guangdong	39	41		5	25	-1	0	31	34	41	42	48	8
7	Guangxi	40	41		3	12	1	0	33	38	41	42	46	4
8	Guizhou	31	32		2	6	0	-1	25	29	32	32	34	3
9	Hainan	20	20		2	5	0	0	15	19	20	22	24	3
10	Hebei	71	71		6	41	0	0	58	67	71	75	80	8
11	Heilongjiang	34	31		8	57	3	2	26	29	31	36	54	6
12	Henan	62	62		6	32	0	0	51	60	62	66	71	6
13	Hubei	52	53		4	13	0	-1	44	50	53	54	58	4
14	Hunan	47	47		3	9	-1	0	42	44	47	50	53	6
15	Inner Mongolia	28	28		3	8	-1	0	24	25	28	29	33	4
16	Jiangsu	63	64		5	28	1	-1	50	60	64	66	70	6
17	Jiangxi	41	41		4	16	0	0	34	38	41	44	50	6
18	Jilin	41	39		7	53	3	2	34	37	39	44	61	6
19	Liaoning	45	46		5	30	0	1	37	42	46	48	58	6
20	Ningxia	44	44		4	19	-1	0	37	40	44	47	50	7
21	Qinghai	33	32		4	16	0	1	27	30	32	36	41	6
22	Shaanxi	44	44		4	13	1	0	36	42	44	46	52	4
23	Shandong	65	66		7	50	1	-1	49	63	66	70	74	7
24	Shanghai	59	59		6	31	-1	0	49	55	59	63	68	8
25	Shanxi	42	42		4	13	0	0	35	41	42	44	49	3
26	Sichuan	42	41		5	24	0	0	31	39	41	45	50	6
27	Tianjin	77	78		9	85	0	0	58	72	78	83	91	11
28	Xinjiang	49	48		7	48	-2	0	39	42	48	56	59	14
29	Yunnan	20	20		2	3	1	-1	16	19	20	21	23	2
30	Zhejiang	44	44		3	8	0	1	40	42	44	45	50	3



	Waste-Water													
	Province	Mean	Median	Mode	St. Dev.	Variance	Kurt.	Skew	Min	1Q	2Q	3Q	Max	IQ Range
1	Anhui	2104	1847		494	24370036	-2	0	1483	1687	1847	2543	2806	857
2	Beijing	1309	1403		227	5162337	-1	0	981	1078	1403	1455	1664	377
3	Chongqing	1450	1451		185	3435517	9	3	1281	1342	1451	1458	2021	116
4	Fujian	2425	2385		302	9142319	2	1	1930	2270	2385	2569	3162	299
5	Gansu	546	512		99	978509	-2	0	423	452	512	650	671	198
6	Guangdong	7553	7230		1270	161171991	-1	0	5417	6774	7230	8625	9383	1851
7	Guangxi	2576	2456		484	23395739	-1	1	1932	2201	2456	3055	3454	854
8	Guizhou	754	608		233	5415488	-1	1	515	557	608	931	1128	374
9	Hainan	370	362		27	74865	3	1	331	353	362	375	441	22
10	Hebei	2614	2625		416	17295888	-2	0	2067	2229	2625	3058	3109	829
11	Heilongjiang	1300	1186		205	4190697	-2	0	1090	1110	1186	1496	1626	386
12	Henan	3488	3587		655	42955514	-2	0	2507	2965	3587	4037	4335	1072
13	Hubei	2701	2708		275	7584679	-1	0	2315	2466	2708	2931	3138	465
14	Hunan	2758	2681		276	7628973	-2	0	2357	2521	2681	3042	3141	521
15	Inner Mongolia	844	925		234	5487986	-2	0	526	604	925	1047	1119	443
16	Jiangsu	5548	5555		517	26688079	-1	0	4661	5097	5555	5982	6213	885
17	Jiangxi	1705	1607		393	15429462	-2	0	1201	1389	1607	2071	2232	682
18	Jilin	1080	1097		129	1659607	-1	0	869	979	1097	1177	1269	198
19	Liaoning	2266	2210		195	3785883	0	1	1953	2172	2210	2345	2629	174
20	Ningxia	356	373		55	304860	1	-1	238	339	373	389	413	50
21	Qinghai	210	220		33	111742	1	0	143	199	220	226	273	27
22	Shaanxi	1181	1157		300	9004595	-1	0	758	993	1157	1322	1681	328
23	Shandong	4123	4364		982	96426531	-1	0	2640	3343	4364	4946	5599	1603
24	Shanghai	2206	2226		134	1795838	2	0	1933	2192	2226	2241	2483	49
25	Shanxi	1178	1161		204	4160452	-2	0	891	1046	1161	1380	1453	334
26	Sichuan	2822	2627		390	15191188	-1	1	2345	2561	2627	3076	3528	516
27	Tianjin	709	671		152	2301659	-2	0	487	596	671	842	930	246
28	Xinjiang	815	833		160	2560150	-1	0	574	686	833	939	1027	253
29	Yunnan	1190	920		421	17746414	-2	0	752	838	920	1566	1811	728
30	Zhejiang	3761	3948		538	28913986	-1	-1	2813	3381	3948	4201	4338	820



Appendix II - R Code

In this appendix the main steps of the econometric model are described through the R code.

```
#Activate the libraries:
library(geosphere)
library(spdep)
library(rgdal)
library(rgeos)
library(GWmodel)
library(plm)
library(spgwr)

#Define X and Y coordinates:

coordinates = coordinates_data_origin[,c("X","Y")]

#Calculate the geographical distances between coordinates:

distances = distm(coordinates[,c("X","Y")],X[,c("X","Y")], fun= distVincentyEllipsoid)

#Starting from distances, create weighting vectors for each Province.

ProvinceX_distances <- distances["ProvinceX"]
ProvinceX = as.matrix(ProvinceX_distances, ncol=1)

ProvinceY_distances <- distances["ProvinceY"]
ProvinceY = as.matrix(ProvinceY_distances, ncol=1)

...

#Define a Bandwidth for the spatial regression:

Bandwidth="x"

#Creating a weighting vector for each "Province" through a bisquare adaptative Kernel
function:

ProvinceX_gw = gw.weight(ProvinceX, Bandwidth, kernel = "bisquare", adaptive=TRUE)
ProvinceY_gw = gw.weight(ProvinceY, Bandwidth, kernel = "bisquare", adaptive=TRUE)
...

#Create a Weighted Panel Data per each province:

PanelProvinceX = data.frame(Province, ID, Year, (ProvinceX_gw *X1),( ProvinceX_gw
*X2))...)
PanelProvinceY = data.frame(Province, ID, Year, (ProvinceY_gw *X1),( ProvinceX_gw
*X2))...)
```

...

```
#Set a Panel Data structure per each province:

pdataProvinceX <- plm.data(PanelProvinceX, index=c("ID", "Year"))
pdataProvinceY <- plm.data(PanelProvinceY, index=c("ID", "Year"))
...

#Define the 3SLS - GWPR for each Environmental Quality (EQ) index and Province:

eqEQ <- "EQ" ~ RGRPPC + RGRPPC2 + RGRPPC3 | lag(POP) + lag(RGRPPC) +
lag (RGRPPC2) + lag (RGRPPC3) + lag (FDI) + lag (TO) +  lag (EI) + lag (KL)
eqRGRPPC <- RGRPPC ~ "EQ"| lag(CO2)  + lag (L) + lag (K)
Province_X <- plm(list(EQ.Emissions = eqEQ,
                 RGRPPC.Development = eqRGRPPC),
            data= pdataProvinceX, index = 30, model = "random",
            inst.method = "baltagi", random.method = "nerlove",
            random.dfcor = c(1, 1))
summary(Province_X)

eqEQ <- "EQ" ~ RGRPPC + RGRPPC2 + RGRPPC3 | lag(POP) + lag(RGRPPC) +
lag (RGRPPC2) + lag (RGRPPC3) + lag (FDI) + lag (TO) +  lag (EI) + lag (KL)
eqRGRPPC <- RGRPPC ~ "EQ"| lag(CO2)  + lag (L) + lag (K)
Province_Y <- plm(list(EQ.Emissions = eqEQ,
                 RGRPPC.Development = eqRGRPPC),
            data= pdataProvinceY, index = 30, model = "random",
            inst.method = "baltagi", random.method = "nerlove",
            random.dfcor = c(1, 1))
summary(Province_Y)

...
```

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