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THREE ESSAYS ON INNOVATION AND GREEN ECONOMY

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Introduction

This doctoral dissertation encompasses three essays concerning innovation and green economy.
The first two papers addresses the theme of eco-innovation; in particular, the first investigates the main drivers of eco-innovation in OECD automotive industry between 2005 and 2014, while the second provides a "map" of green technologies in OECD and BRICS countries by means of an unsupervised machine learning approach.
The third paper is an ex-post policy evaluation of an innovative and sustainable mobility policy at urban level.

The first paper is an empirical analysis of the determinants driving the so-called "green innovation" transition in the OECD automotive industry, which is measured by patent data.
This study, based on an econometric analysis using a *Negative Binomial* estimation model, highlights that the so-called *technology push* and *market pull* are the current most incisive drivers of the green transition of the automotive industry in OECD countries, while the so-called *institutional push/pull* still lags behind as source of green innovation in the above-mentioned OECD sector, causing an an institutional lock-in.
In fact, the study reveals that the regulations in OECD countries, proxied by the *Environmental Policy Stringency index*, have been been more "technology-following" than "technology-forcing", since they have induced an increase of the production of innovations aimed at improving the efficiency of the conventional technology (brown patents) rather than the development of radical innovations diverging from the incumbent technological trajectory (green patents).
The study also highlights the substitution effect caused by fuel price, which has a positive impact on green technologies in automotive, providing results that are consistent with the main findings in the literature on fuel price.

The second paper aims at tracking the green technological profile of the OECD and BRICS countries by means of an unsupervised machine learning approach, namely the so-called *Self-Organizing Map* (SOM) method, which allows to group countries according to the similarities in their green technological output.
The scope of our SOM-based analysis is to examine clusters features both in quantitative and qualitative terms, to investigate countries technological evolution over time and to verify whether our study is providing evidence in support of a technological paradigm change.
The results reveal a sharp distinction between a small leading group of large and rich countries with a high production of green patents and green specialization in climate change mitigation and a mass of relatively small and poor countries with very low production of green patents and a vast array of specialization profiles in their green profile, but always related with the greening of more traditional areas (rail, oil, soil and water) .
Moreover, our SOM-based study substantially confirms the real technological evolution experienced by the countries, whose green vocation tends to show constant patterns over time, apart from those of BRICS.
The main conclusion is that, based on our data, there is a current transition toward more sustainable technological solutions, but since countries that are leading the way in terms of green patents productivity are specialized in technologies that are still integrated in the old technological regime, we are not facing a technological paradigm change.

The third paper evaluates the environmental impact of an innovative sustainable mobility policy in Paris region, with the aim to provide a meaningful ex-post policy assessment with relevant policy-making implications.
The study consists in an econometric analysis based on a *Difference in Difference* estimation model, which investigates the environmental effects of the introduction of the electric car-sharing service *Autolib'*, in Paris region in 2011, revealing that the above-mentioned public-private service has significantly contributed to the reduction of the annual average concentration of some of the main urban pollutants, namely PM10, NOx and NO2.
Despite some limitations, the study succeeds in providing interesting scientific information about the environmental performances of the smart service examined.

Essay 1.
Are we breaking the ICE? An analysis of brown and green innovations in OECD countries[1]

[1]This chapter has been developed in collaboration with Prof. Marco Guerzoni and Prof. Nicoletta Corrocher.

Abstract

This paper explores the determinants of brown and green innovations in the automotive industry in OECD countries, with the aim of investigating the existence of a technological paradigm shift in the sector and to study the substitution/complementarity between different types of innovations.
Relying on a dataset of 35 OECD countries between 2005 and 2014, we look at technology-push, demand-pull and regulatory drivers of different types of innovations in the sector.
We find that technological push and demand pull drive a decrease in the development of brown innovations and an increase of green innovations.
On the other hand, we show that the institutional push/pull is still lagging behind as a driver of the ecological transition of the automotive industry, since it causes an increase of brown patents, with no substantial effect on the quantity of green patents, revealing the presence of an institutional lock-in.

Keywords: eco-innovation, automotive, patents, policy evaluation
JEL: O30, Q55

1 Introduction

Automotive is a relevant sector in the economy of most of developed and emerging countries, and, as a capital-intensive and knowledge-intensive industry, its innovation activities play a key role in driving successful and sustainable economic growth.
Automotive industry has in fact a significant impact on both the economy and the environment.
The average annual turnover of the world automobile industry is more than 2.75 trillion Euro, which corresponds to 3.65 percent of world GDP, while the share of the industry in the GDP of developed countries ranges from 5 to 10 percent, accounting for 3 percent of US GDP, and representing 6.8 percent of EU GDP. (Saberi, 2018)
Moreover, in the economy of developed countries, growth in the automotive industry by 1 percent is estimated to cause a GDP growth of 1.5 pc; furthermore, modern experts of the automotive market forecast that the annual growth rates of the world automotive market will be about 3.6, which roughly corresponds to the dynamics of world GDP. (Saberi, 2018)
The industry is also a major innovator, investing more than 84 billion euros in research, development and production and thus placing third among the sectors with the greatest R&D expenditures, after pharmaceuticals and biotechnology and production of process equipment. (Saberi, 2018)
As far as the environmental impact is concerned, transports are large contributors to global greenhouse gases emissions. According to the Stern Review, in 2000 14 percent of the world's greenhouse emissions stemmed from transport alone, a figure that has increased over the past fifteen years. (Stern and Stern, 2007; IEA, 2019)
Along with GHG emissions, specifically CO2 emissions, transports are responsible for the production of local pollutants, such as particulate matter (PM), hydrocarbons (HC), nitrogen oxides (NOx), sulphur dioxide (SO2), carbon monoxide (CO) and ground-level ozone (O3), in charge of heavily affecting urban air quality. (Krzyzanowski and Cohen, 2008)
In light of the above-mentioned evidence, the innovation activity in the automotive sector has a primary role for green growth, with the purpose of tackling climate change and the most crucial environmental challenges.
The innovative activity of this sector is a crucial component for the upsurging "mobility challenge", which is characterised not only by the discussion around the paradigm clash between the traditional forms of ICE engines and the electric/green mobility, but also by the reflection on the car's utility, with the comparison between the ownership and ridership approach. (Calabrese, 2016)

The paper aims at investigating the main determinants of innovations in the automotive industry, by focusing on the analysis of “technological push”, “demand pull” and “institutional push/pull” factors at the country-level.
In particular, we intend to understand which are the most impactful drivers of eco-innovation in the industry within OECD countries.
While most of the existing literature examines the determinants of eco-innovation in automotive industry by focusing on single drivers or specific policies at firm-level, this study intends to contribute to the existing literature by performing a country-level analysis that explicitly investigates the effect of all the three sets of determinants of eco-innovation using an innovative dataset for patent data: OECD iLibrary.

The rest of the paper is structured as follows.
Section 2 outlines the theoretical framework, identifying the main determinants of eco-innovations with specific reference to the automotive sector and presenting the paper’s hypothesis. Section 3 and 4 describe respectively the empirical model and the data. Section 5 discusses results, while section 6 concludes.

2 Eco-innovations in the automotive industry: theory and hypothesis development

Eco-innovations are innovations that consist of new or modified processes, practices, systems and products which benefit the environment and contribute to environmental sustainability. (Rennings, 2000; Oltra et al., 2008a) Since eco-innovations cannot be defined only in terms of their absolute environmental impact, but also in reference to alternative technologies, the most precise definition of eco-innovation is the one provided by the MEI report[1]: "The production, assimilation or exploitation of a product, production process, service or management or business methods that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives". (Kemp and Pearson, 2008)

The literature has discussed at length the drivers of eco-innovations and has highlighted the importance of supply-push, demand-pull and regulatory factors for their development. (Horbach, 2008; Horbach et al., 2012)
As far as supply-push factors are concerned, both technological opportunities and firms' strategies play an important role. (Ghisetti and Rennings, 2013; Cecere et al., 2014) Some studies look at the potential of specific alternative technologies to transform the existing technological regime. (Janssen and Jager, 2002) In this respect, many acknowledge the role of stimulating the development of technological niches to escape from the dominant pollution-intensive paradigm.
Firms are the most important actors in the sustainable growth process, as they are actively engaging in the development of green innovations (De Marchi, 2012; Kesidou and Demirel, 2012; Dangelico, 2016) and in the form of adoption of low-carbon energy solutions for their businesses (Pinkse and Van den Buuse, 2012; Albino et al., 2014; Bodas-Freitas and Corrocher, 2019).
In terms of demand-side factors, firms may respond to the market need for eco-friendly products/services, especially when consumers put particular value to "green brands". (Rennings et al., 2006; Rehfeld et al., 2007; Kammerer, 2009; Dangelico and Pujari, 2010; Horbach et al., 2012; Lannelongue and González-Benito, 2012)
Finally, regulation has been identified as an important source of environmental innovation, due to the well-known double externality problem. (Rennings, 2000; Cecere et al., 2014)

[1]'Measuring Eco-innovation', United Nations University, 2008

The beneficial impact of environmental innovations makes not only their development, but also their diffusion always socially desirable, creating a twofold obstacle, or market failure, for firms to invest in environmental innovation, since the private return on R&D in environmental technology is less than its social return both in the production and in the diffusion phase. (Oltra et al., 2008a; Rennings et al., 2006; Horbach et al., 2012)
Several empirical studies have proved that environmental regulation can have a positive impact on firms' inventive activities, providing evidence in favour of the weak version of the "Porter's hypothesis", by Porter and Van der Linde (1995). (Lanoie et al., 2011; Johnstone et al., 2012; Ambec et al., 2013; Hottenrott and Rexhäuser, 2015; Kounetas, 2015)
On the other hand, regulation can be source of institutional lock-in, as highlighted in Foxon (2002). Furthermore, environmental regulation is highly heterogeneous across countries and companies that develop and adapt green technologies in response to a heterogeneous set of incentives. (Tatoglu et al., 2014; Kawai et al., 2018; Marin and Zanfei, 2018)

The development of green innovations is particularly relevant in the automotive industry, which is not only an important sector in the economy of both developed and emerging countries, but is also the locus of innovation activities that play a key role in the process of sustainable growth (Lee and Berente, 2013).

Car manufacturers and suppliers are responsible for the development of green innovations in the sector. On the one hand, major producers from Europe, US, Japan and South Korea have carried out R&D activities with the aim of reducing emissions. (Haščič and Johnstone, 2011; Berggren and Magnusson, 2012; Dechezleprêtre et al., 2015) On the other hand, domestic companies from new comer countries (especially from China) have started innovating in green technologies, even if they still rely substantially on the technology acquired from larger producers. (Chin, 2010)

Several studies have investigated eco-innovation in automotive, exploring its main determinants and patterns of evolution.
Haščič et al. (2008), for instance, finds that environmental technologies in the automotive industry are positively affected by gasoline prices and regulatory standards, with domestic policies exerting a greater influence on foreign innovations than on domestic innovation, because of the anticipatory behavior of domestic firms with respect to the upcoming regulations.
These results are confirmed by the work of Aghion et al. (2016) investigating the impact of carbon taxes on direct technological change, which detects

a positive and significant effect of higher tax-inclusive fuel prices on 'clean' innovations, while a negative and significant effect on 'dirty' innovations.
Aghion et al. (2016) also prove the existence of path dependency in automotive innovation patterns: firms that are innovators in 'dirty technologies' find it more profitable to keep investing and innovating in dirty technologies, instead of 'going green'.
Other scholars, Barbieri (2015, 2016), have confirmed that fuel prices represent one of the main drivers of the technological efforts concerning green automotive technologies, along with R&D subsidies and predictable and credible policy interventions in the form of regulatory instruments (e.g. European emission standard, CO2 targets).
Bergek et al. (2014) provides a survey on the type of innovation output resulting from different type of environmental policies in automotive and energy sectors:

- *Incremental innovation*, featuring slight technological changes, aimed at improving the standard available technology;
- *Modular innovation*, featuring the addition of new modules to the standard technology, with the aim of improving its efficiency and performances;
- *Architectural innovation*, featuring a completely new design of the established technology, with the recombination of existing components;
- *Radical innovation*, characterised by the introduction of entirely new components, changing the structure and sometimes the purpose of the established technology, paving the way for a technological paradigm change and the creation of a new technological trajectory.

By observing the effect of the implementation of specific policies on innovation outcomes in automotive literature, Bergek et al. (2014) highlight that, general policies, such as fuel taxes and emission regulations, mainly result in incremental and modular innovations (catalytic converters, fuel saving modules, clean diesel technologies). On the other hand, technology-specific policies, e.g public procurement and the so-called "zero-emission vehicle rule", induce more architectural and radical innovations, such as the development and diffusion of hybrid-electric and fully electric vehicles.
Alongside with the development of green technologies in automotive sector, their diffusion across countries has rose increasing interest among scholars.
For instance, Dechezleprêtre et al. (2012) examine the impact of the regulatory distance on the transfer of environmentally sound technologies (EST) in

automotive, discovering that the number of new automotive environmentally-sound technologies increases when the difference between two countries in regulatory levels decreases. Moreover, the paper points out that, the regulatory distance between the source country and the export market of the recipient country has a negative and statistically significant effect on ESTs.

While the majority of the studies focuses on the determinants of innovation development and diffusion, Dijk and Yarime (2010) identifies three major sources of innovation lock-in through path dependency in the automobile sector: demand-side lock-ins (consumers seeking for the lowest price or highest performance vehicles), supply-side lock-ins (firms having difficulties in disinvesting from dirty technologies) and regulatory-side lock-ins (regulations supporting existing technologies -technology-following- instead of stimulating the shift towards new ones -technology-forcing-).

Dijk et al. (2013) indicate the major factors steering the emergence of an electric mobility trajectory: change in the fuelling infrastructures, change in the global market (demand pull), evolution of energy prices and climate policies (institutional drive), variation in the electricity sector (technological push) and in the utility value of vehicle, which is related to the overall mobility concept.

The variation of the utility value of the vehicle as factor for change in mobility is highlighted as a key factor also in Calabrese (2016), which outlines three possible automotive scenarios deriving from the current greening pattern of the automotive industry: *diversity*, *progressiveness* and *rupture*.

The *'diversity scenario'* is an evolution of the current scenario, characterized by five groups of countries with different energy preferences: less polluting engines, agro fuels, natural gas, plug-in hybrids and electric vehicles, and pollutant reduction, with fuel cell perspectives.

This scenario leads to a greater differentiation of the world's car market, a greater complexity of the innovation platforms, more R&D investments, more difficulties in pursuing the 'volume and diversity' and 'permanent reduction of the costs' profit strategies and the emergence of some market niches, where newcomers or 'born again' can find their space to thrive or survive. (Calabrese, 2016)

The *'progressiveness scenario'* plans a transition from fuel-efficient engines to electric motors, through agro-fuelled natural gas propelled engines, to hybrid and plug-in hybrid engines. The progression will be led by three rates of transition: the rate of depreciation of investments, the technological improvement and rate of natural renewal of world stock of cars.

This scenario has the potential to transform in an 'all at once' scenario, if

any of the disruptive factors governing global automotive dynamics, such as oil price, global warming, the explosion of an emerging Chinese or Indian car manufacturers or an increasing government pressure, prevails.
The *'rupture scenario'* is the most radical scenario and encompasses two phases. In the first phase, the rapid shift to electric vehicles will involve only some usage modes (short-run, urban rides) and types of users (rental car services, local delivery companies, household's second car, urban riders), who will be offered grants, subsidies and special discounts to be electric cars early-adopters.
The reduction of energy and technology prices will introduce a second phase, with the adoption of electric vehicles for all usages (long- and short-run rides) and by all users (urban dwellers and long-run travellers), without any further institutional intervention.

Table 1 summarizes the determinants, drivers and drawbacks of eco-innovation in automotive industry.

DETERMINANTS	**DRIVERS**	**DRAWBACKS**
TECH PUSH	Green technological opportunities	Technological lock-in
DEMAND PULL	Customers' willingness to pay for fuel efficiency	cost, comfort
INSTIT DRIVE	Fuel taxes and regulatory standards	Institutional lock-in

Table 1: The drivers of eco-innovations

Our paper intends to examine the evolution of the patents production of the automotive industry in the main OECD countries, over a ten year period (2005-2014).
This period has been characterized by relevant events for the automobile sector, such as the economic financial crises of 2008, which had dramatic consequences on the car industry and market, and important changes in cars regulations (especially in the EU area).
These events offer an interesting backdrop to explore the evolution of the automobile industry and investigate the possible emergence of the scenarios outlined by Calabrese (2016).
Against this backdrop, the aim of the paper is to investigate whether the main technological determinants (technological push, demand pull and institutional push/pull) have caused the reduction of the production of brown innovations and the parallel increase of green innovations in the OECD automotive industry, inducing the emergence of the progressiveness or rupture

scenarios, as forecasted by Calabrese (2016).

We are developing three hypotheses building on the existing literature.
The first hypothesis concerns the role of technology-push factors in driving green vs. brown innovations in the sector. We explore whether the *national technological capabilities* impact the production of green and non-green innovation in the automotive industry, measured by patents data.
Hypothesis 1: national technological capabilities in green domains generate a decrease in BROWN TECHs and an increase in GREEN TECHs

The second hypothesis refers to the role of demand-pull factors in stimulating the innovation pattern of the automotive industry, as highlighted in the literature. In particular, we look at how the *national demand for cars* impacts the production of green and non-green innovations in the automotive industry, measured by patents data.
Hypothesis 2: national demand for cars positively affects the development of GREEN TECHs and negatively affects the development of BROWN TECHs.

Finally, the third hypothesis refers to the role of policies and regulation. In particular, the *stringency of regulation* is often acknowledged as a significant trigger for innovation (Porter and Van der Linde (1995); Wagner (2003); Ambec et al. (2013); Barbieri et al. (2016)). On the basis of the existing literature, we look at the impact of the stringency of regulation on the development of green vs. brown technologies, measured by patent data.
Hypothesis 3: the stringency of regulation positively affects the development of GREEN TECHs and negatively impacts the development of BROWN TECHs

3 The empirical model

In order to investigate the relationship between eco-innovation and its determinants, we use a function taking the following form:

$$\text{Innovation output} = f\ (\text{Innovation Inputs})$$

It relates an innovation output to a vector of innovative inputs, which is made up of the Technological Push, the Demand Pull and the Institutional Push/Pull proxies.

As it is standard in the literature, we measure country's eco-innovation capability through the number of patents applications: we distinguish brown and green patents (see section 4.2.1).
We use count data models and estimation methods, since they are more appropriate than linear models when dealing with dependent variables that take on non-negative integer values, as in our case.
Our estimation method is the maximum likelihood for the negative binomial distribution. We prefer a negative binomial model over Poisson models as the equality between the mean and the variance of the dependent variables assumed by Poisson models is not verified in our data. The distribution of the number of patents applications, in fact, is substantially over-dispersed, with variance much higher than the mean (see Table)
In the negative binomial regression, the expression relating the mean of the dependent variables with the exposure time and the set of regressors takes the following form:

$$\mu = exp(ln(t_i) + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i}) \tag{1}$$

By adding entity fixed effects in order to control for unobserved countries heterogeneity, the above-mentioned equation takes the following form:

$$\mu = exp(ln(t_i) + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i}) + \gamma_i \tag{2}$$

After performing an appropriate test, we also include time fixed effects for the regression on green patents, while we do not include them in the regression on brown patents. The formula for the estimation including time fixed effects is the following:

$$\mu = exp(ln(t_i) + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i}) + \gamma_i + \zeta_t \tag{3}$$

Finally, to help reduce the risks of spurious relationships, we lag all the explanatory variables by two years.
Our model also includes a set of relevant controls (GDP, GDP per capita and fuel price), which are not lagged.

4 The data

The present section describes the datasets and the variables used, showcasing relevant summary statistics and graphical analysis.

4.1 The data sets

The dataset is composed by observations on 35 OECD countries over a 10 year time frame, from 2005 to 2014, resulting in a strongly balanced panel.
Most data come from the OECD iLibrary and Statistics databases, among which we used:

- OECD Environment Statistics (1), *Patents in environment-related technologies: Technology development by inventor country* (OECD ENV-TECH, 2019);
- OECD Environment Statistics (2), *Environmental policy: Environmental Policy Stringency index* (OECD EPS, 2019);
- OECD-STAN, *STructural ANalysis* database (OECD STAN, 2019) ;
- OECD-ANBERD, *Analytical Business Enterprise Research and Development* database (OECD ANBERD, 2019) ;
- OECD-BTDIxE, *Bilateral Trade in Goods by Industry and End-use* database (OECD BTDIxE, 2019)

Along with the OECD datasets, we have employed information retrieved from the dataset of the International Organization of Motor Vehicle Manufacturers (OICA, 2019).

4.2 The variables

The dependent variable consists in the number of registered patents in OECD countries within the automotive sector, divided by type of technology.

Patents are the OECD recommended measurement approach for eco-innovation, since they measure technological innovation by definition, focusing on the output of inventive process. (Oltra et al., 2008b; Haščič and Migotto, 2015) Further reason to use patent data as proxy for innovation, and specifically for eco-innovations, is that they can be disaggregated into specific technological fields, a fundamental feature to study environmental innovation.
Additional motivation derives from their commensurability, possibility to measure intermediate outputs, wide availability and quantitative nature. (Haščič and Migotto, 2015)

We have retrieved data on patents in automotive sector from OECD ENV-TECH (2019), whose focus is on environmental type of technological patents; the typologies of automotive-specific technological patents are those listed in Table 2, where they are associated to a class of innovation.

Class of technology	**Class of Innovation**
. Internal Combustion Engine (ICE)	*BROWN*
. Emissions abatement from mobile sources	*BROWN*
. Fuel efficiency-improving vehicle design	*BROWN*
. Hybrid vehicles	GREEN
. Electric vehicles	GREEN
. Electric charging systems	GREEN
. Fuel cell systems	GREEN

Table 2: Technologies by eco-innovation class

Based on Aghion et al. (2016)[2], these technologies have been grouped in two categories, according to their green content and innovative purpose. (see Table 3)

Eco-Innovation	**Innovation**	**Technology**
BROWN	*incremental & modular*	ICE, tail technologies, fuel efficiency
GREEN	*architectural & radical*	hybrid, BEV, ECS, fuel cell

Table 3: Technologies by type of innovation & eco-innovation class

[2] Aghion et al. (2016) actually identifies three types of eco-innovation: green, grey and brown, but here, for the sake of simplicity, we group technologies in just two categories: green and brown

Our first explanatory variables are the so-called *Technological Push* and the *Demand Pull*, that we capture by means of appropriate proxies.
As a proxy for the *Technological Push* we use the ratio between the total environmental patents and the total number of patents per country.
Both data for environmental patents and total patents are retrieved from (OECD ENV-TECH, 2019).
The proxies for the *Demand Pull* are the number of car sales and the household expenditures for the car, whose data are retrieved from (OECD BTDIxE, 2019).
As a proxy for the *Institutional Push/pull* we use the Environmental Policy Stringency Index (EPS), which is a country-specific and internationally-comparable measure of the stringency of environmental policy. [3]
The index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution.
We consider EPS able to capture the level of policy stringency in the transport sector as it includes a CO2 tax indicator, a NOX tax indicator and a Diesel tax indicator. Data on EPS are retrieved from (OECD EPS, 2019)

Furthermore, we employ two classical economic indicators, GDP and GDP Per Capita, as controls for the trends respectively in the supply side and the demand side.

Finally, we include as control also the Fuel Price, since it is a relevant factor affecting innovation production in the automotive industry, as shown by several empirical works Horbach (2008); Aghion et al. (2016); Barbieri (2016).
Data on GDP and Fuel Price are retrieved from OECD online datasets.

Table 4 contains an exhaustive summary of the variables, with their measurement function, type and role in the regressions.

[3] Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour.
The index ranges from 0 (not stringent) to 6 (highest degree of stringency) and it covers 28 OECD and 6 BRIICS countries for the period 1990-2012.

Variable	Measure	Type	Role
GREEN PAT (X4)	Number of *green patents*	count	dependent v.
BROWN PAT (X3)	Number of *brown patents*	count	dependent v.
ENVI / TOT PAT	Ratio btwn Envi and Total patents	count	TECH PUSH
CAR SALES	number of cars sold	count	DEM PULL
HH EXP CAR	Household Expenditure for Car	count	DEM PULL
EPS	Environmental Policy Stringency	count	INSTIT
GDP	Gross Domestic Product	count	ECON
GDP P-C	Gross Domestic Product Per Capita	count	ECON
FUEL PRICE	Road Fuel Price	count	ECON

Table 4: The variables

4.3 Descriptive statistics

The data set used in the empirical analysis is a country-level data set, consisting in 350 country-year observations.

Table 5 provides summary statistics about the dependent variables at disaggregated level, which are the number of patents in 7 different technological categories: *tail technologies, internal combustion engines, fuel efficiency technologies, hybrid, battery electric vehicles, electric charging systems* and *fuel cells.*

INSERT TABLE 5 AROUND HERE

Tail technologies represents the category with the highest number of registered patents (298.36) on average, followed by *internal combustion engines*, ICE, (114.31) and *battery electric vehicles*, BEVs, (85.69).
Battery electric vehicles also have the maximum number of registered patents (1833.57), followed by *tail technologies* (1732.75) and *internal combustion engines* (1204.75)
All the investigated technologies have a minimum value of patents equal to 0; moreover the investigated technologies also have very high values of variance, greater than their mean values.

Table 6 outlines summary statistics about the dependent variables at aggregated level, revealing that, as expected, the average number of brown technologies is higher than the average number of green technologies.
The variance is always higher than the mean for both the categories of

patents, revealing the presence of over-dispersed data, which suggest the use of a negative binomial model.

INSERT TABLE 6 AROUND HERE

Table 7 shows the relevant summary statistics for the explanatory variables, which include *Technology Push*, *Demand Pull*, *Institutional Push/Pull* and the economic variables.

INSERT TABLE 7 AROUND HERE

We highlight that the ratio between countries' green patents and total patents is on average 10%.
As far as the demand side is concerned, the average number of car sales is equal to 840.653, while the average household expenditure for a car is equal to 27.000 US dollar.
Looking at the economic indicators, the average GDP value is 1.322.106 US dollar, while the average GDP per Capita is equal to 34.629 US dollar. The average fuel price[4] is equal to 1.7 US Dollar.

4.4 Graphical analysis

Figure 1 shows the trends of brown and green technologies in the OECD automotive industry between 2005 and 2014.
As expected, the initial level of brown patents is much higher than the level of green patents. However, while the brown patents show a substantial stable trend with a slight increase over time, green patents display a steep increasing trend until 2011, when they start a sudden sharp decrease.

Figure 2 shows the trend of the different patent typologies over time.
Patents of the so-called "tail technologies" (emission abatement technologies) display a declining pattern (red line in the graph).
ICE patents (yellow line) show a substantially stable pattern, with a slight increase over time.
Patents for electric vehicles (light green line) experience a remarkable increase until 2011, then they slightly decline from 2012 onward.
A similar trend is visible for patents of electric components (violet line),

[4] Price of premium unleaded 98 RON (litre) gasoline

which display a rising pattern until 2011, then they slightly decline from 2012 onward.
Patents of Hybrid (green line), fuel efficiency (light blue line) and fuel cell (pink line) technologies show substantially stable patterns over time.
To sum up, we can observe that among the so-called "brown technologies" only emission abatement technologies follow a declining trend, while ICE techs display a stable and slightly increasing trend.
On the other hand, among the so-called "green technologies", electric vehicles and components have a rising trend, while the other technological types of patents show substantially stable patterns.

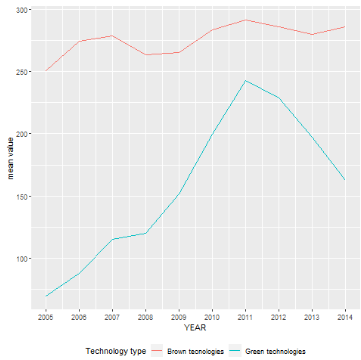

Figure 1: Brown and Green Technological Trends

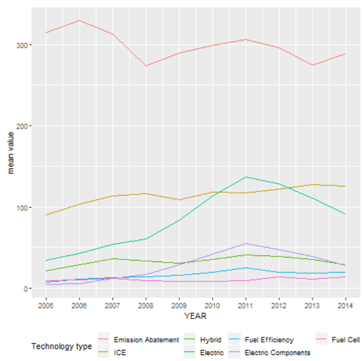

Figure 2: Technological trends by type of technology

5 Results

5.1 Estimations and interpretation

Table 8 shows the results of the regressions with the *Negative Binomial* model. All the estimations include country dummies and the following explanatory variables are lagged by two years: ratio between environmental and total patents, car sales, share of expenditures for car sale and environmental policy stringency index.
Controls, namely GDP, GDP per capita and fuel price, do not have lagged values.
Time fixed effects are included in the regression on green patents after an appropriate test.

INSERT TABLE 8 AROUND HERE

First, we test *Hypothesis 1*, that is, whether the so-called "technological push", proxied by the *ratio between environmental and total patents*, has reduced the number of brown innovations and increased the number of green innovations in the automotive sector of the OECD countries between 2005 and 2014.
We observe that the *ratio between environmental and total patents* has a positive and statistically not significant coefficient with respect to the brown innovations, implying that there is no statistically significant effect of the "technological push" on the production of polluting technologies for the time period considered (2005-2014).
On the contrary, we observe that the *ratio between environmental and total patents* has caused a positive and statistically significant effect on green innovations, meaning that the "technological push" has induced an increase in automotive sustainable technologies.
To sum up, the "technological push" has caused a statistically significant increase of green patents, while it did not steer any reduction in the production of brown patents during the time period considered.

Then, we test *Hypothesis 2*, that is, whether the so-called "demand pull", proxied by the variables *car sales* and *share of expenditures for car purchase*, has caused a decrease in the number of brown technologies and an increase in the number of the green innovations in the automotive sector of the OECD countries between 2005 and 2014.

We find that the variable *car sales* has caused a statistically significant increase of both brown and green technologies, while the variable *share of private expenditures for car purchase* has caused a statistically significant decrease of brown technologies, while it has no substantial effect on green technologies.
To sum up, there is some empirical evidence showing that the "demand pull" has caused a statistically significant increase of green patents through *car sales* and a statistically significant decrease of brown patents, via the *share of private expenditures for car purchase*.
These results can be explained by the shrinking of the conventional cars market, due to its overcrowding and the financial crisis, which severely hit OECD households between 2008 and 2011, and the growing awareness and demand for less polluting (brown technologies) or pollution-free (green technologies) cars, also thanks to the indirect effect of most stringent car regulations.

Finally, we test *Hypothesis 3*, that is, whether the "institutional push/pull", proxied by the *Environmental Policy Stringency Index* (EPS), has caused a decrease in the number of brown technologies and a parallel increase of the green innovations.
We find that EPS has produced a statistically significant increase of brown patents (+0.28), while it has no significant effect on green patents.
This result can be due to the fact that most of the environmental regulations enforced during the time period considered have been relatively more "technology following" than "technology forcing" (Dijk and Yarime, 2010).
In fact, most of the car regulations, especially those promoted in the European Union, have been intended to encourage the improvement of the efficiency of the existing conventional (dominant) technology (e.g. EU introduction and evolution of the so-called "EURO standards"), instead of pushing the development of radical innovations (e.g. US with the California ZEV Program).

We conclude our analysis of the results by highlighting that while GDP and GDP-PC has had no statistically significant effect on the production of neither brown nor green technologies, fuel price stands out as factor that has had a significant impact on the production of green technologies, producing a relevant substitution effect. Morevover, the result for the fuel price is consistent with the main findings on the topic in the literature (Aghion et al., 2016).

5.2 Interpretation of the negative binomial coefficients: Incidence Rate Ratio

In the negative binomial model of estimation, the regression coefficients are interpreted as a difference between the logs of expected counts.
Formally, this can be written as follows:

$$\beta = log(\mu_{x0+1}) - log(\mu_{x0}) \tag{4}$$

where β is the regression coefficient, μ is the expected count and the subscripts represent a one unit change in the predictor variable.
Thanks to the logarithm properties, the difference of two logs is equal to the log of their quotients, that is:

$$log(\mu_{x0+1}) - log(\mu_{x0} = log(\mu_{x0+1}/\mu_{x0}) \tag{5}$$

Therefore, the parameter estimate can be also interpreted as the log of the ratio of expected counts, introducing the term "ratio" in our estimate interpretation.
Moreover, our count variable can be technically interpreted as a rate: the number of patents per year. Hence, we could also interpret the regression coefficients as the log of the rate ratio, introducing the term "rate" in our estimate interpretation.
Finally, the rate at which events occur is called incidence rate; thus, we are able to interpret the coefficients also in terms of *incidence rate ratio*.
In our study, the *incidence rate ratio* means that if a country experiences an increase of its explanatory variable by one unit, the rate for the dependent variables is expected to increase or decrease by a factor given by the IRR value.
The bigger the IRR is, the larger is the effect of the explanatory variable on the dependent variable.
At the end of Appendix A, there are tables showing the *incidence rate ratio* for brown and green technologies.

6 Conclusions

In this paper we investigate the impact of the main innovation determinants on the eco-innovation outcome in the automotive industry.
As innovation determinants, we used proxies of the technology push, demand pull and institutional push/pull, while we employed patent data to capture the innovation outcome.
The aim is to verify whether innovation drivers have been able to produce a decrease in the production of brown patents, while stimulating an increase of the production of the green patents, favouring the green transition of the automotive industry towards more sustainable forms of mobility.
Our empirical investigation relies on data retrieved from OECD and OICA databases and it is based on the implementation of a negative binomial estimation model to assess the impact of the above-mentioned determinants, while controlling for some relevant controls (GDP, GDP P-C and fuel price).
Our results reveal that the *technology push* plays the most significant role in increasing the amount of green solutions in automotive (+10.96).
Simultaneously, the *demand pull* is also key in steering the green transition of the automotive industry; in fact, the present study shows that the demand pull has caused a small, but statistically significant increase of green patents through *car sales* (0.00018) and a significant decrease of brown patents, via the *share of private expenditures for car purchase* (-0.042).
Finally, our empirical investigation shows that the *regulations*, proxied by the Environmental Policy Stringency (EPS) index, are a source of the so-called "institutional lock-in": in fact, EPS is associated with a statistically significant increase of brown patents (+0.28) and no substantial effect on the quantity of green patents.
The study also highlights the role of the fuel price in the green transition of the automotive sector, where it steers a significant substitution effect.
The main policy implication of this study is the need for more effective eco-innovation policies, favouring *technology-forcing* over *technology-following* regulations, in order to break the current institutional lock-in.
A more resolved institutional support to non conventional engines would be key also to drive the automotive industry from a diversity/progressiveness scenario, where it still evolves along the traditional technological trajectory, to a rupture scenario, embracing a radically new technological pathway.
This study also opens up stimulating avenues for further research. Further studies could examine automotive eco-innovation trends in emerging countries, such as *BRICS*, where automotive industry is recently booming and experiencing an acceleration in the development of *green tech* solutions.

A Appendix

Table 5: Summary statistics: Dependent Variables -disaggregated-

Variable	**Mean**	**Variance**	**Min**	**Max**	**N. Obs**
ICE	114.31	72577.77	0	1204.75	350
Tail Tech	298.36	285385.5	0	1732.75	170
Fuel Efficiency	16.48	1756.93	0	277	350
Hybrid	33.19	8415.61	0	595	350
BEV	85.69	60964.8	0	1833.57	350
ECS	27.95	7125.91	0	658	350
Fuel Cell	10.69	864.95	0	159	350

Table 6: Summary statistics: Dependent Variables -aggregated-

Variable	**Mean**	**Variance**	**Min**	**Max**	**N. Obs**
Brown technologies	275.7081	306907.1	0	2862.82	350
Green technologies	157.5132	192488.1	0	3202.9	350

Table 7: Summary Statistics: Explanatory Variables

Variable	**Mean**	**Variance**	**Min**	**Max**	**N. Obs**
Ratio Green/Total patents	.101849	.001009	.0242181	.2504784	350
Car sales	840.653	2,065,685	2.113	7,761.592	350
HH Exp. Car	27.51	50.28	7.2	44	290
GDP	1322106	7.11e+12	11048.36	1.75e+07	330
GDP P-C	34,629.75	2.07e08	14.9	101,274.9	350
Fuel price	1.71977	.3137752	0.652	3.295	165

Table 8: The impact of technology push, demand pull and institutional push/pull on brown and green patents production

	(1) BROWN_TECHS	(2) GREEN_TECHS
RATIO ENVI/TOT PATENTS	-2.197262	10.969465***
	(2.403756)	(3.513629)
CAR SALES	0.000180**	0.000180***
	(0.000085)	(0.000053)
SHARE HH EXP CAR	-0.042732***	0.008875
	(0.014980)	(0.014543)
EPS	0.286257**	0.014436
	(0.114414)	(0.069105)
GDP	-0.000041	0.000047
	(0.000070)	(0.000049)
GDP PC	-0.009372	0.086830
	(0.056450)	(0.063278)
FUEL PRICE	0.147461	1.002103***
	(0.215972)	(0.376695)
Country dummies	YES	YES
Year dummies	NO	YES
cons	3.256036***	-0.635474
	(0.936747)	(1.296538)
N	110	110

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Incidence Rate Ratio for brown and green technologies

BROWN TECHNOLOGIES				
Variable	**IRR**	**Std. Err.**	**z**	**Pr**$> \|z\|$
Ratio Green/Total patents	0.111	0.26	-0.91	0.361
Car sales	1.00018	0.000085	2.12	0.034
HH expenditures car purchase	0.95	0.014	-2.85	0.004
EPS	1.33	0.15	2.50	0.012
GDP	0.999	0.00007	-0.59	0.558
GDP PC	0.99	0.055	-0.17	0.868
Fuel price	1.15	0.25	0.68	0.495
constant	25.94	24.30	3.48	0.001
GREEN TECHNOLOGIES				
Variable	**IRR**	**Std. Err.**	**z**	**Pr**$> \|z\|$
Ratio Green/Total patents	58073.53	204048.8	3.12	0.002
Car sales	1.00018	0.000053	3.39	0.01
HH expenditures car purchase	1.008915	0.014	0.61	0.542
EPS	1.014	0.070	0.21	0.835
GDP	1.000047	0.000048	0.96	0.335
GDP PC	1.090	0.069	1.37	0.17
Fuel price	2.72	1.02	2.66	0.008
constant	0.529	0.68	-0.49	0.62

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Essay 2.
The evolution of the countries green technological profile: an unsupervised machine learning approach [1]

[1]This chapter has been developed in collaboration with Prof. Marco Guerzoni and Prof. Nicoletta Corrocher.

Abstract

The aim of this paper is to track the green technological evolution of OECD and BRICS countries using green patent data over a 25 year period through an unsupervised machine learning approach, the so-called *Self-Organizing Map* (SOM). The approach allows to cluster countries according to their green technological similarities, providing an insightful taxonomy.
The results reveal a sharp distinction between a small leading group of large and rich countries with a relevant green patenting activity and green specialization in climate change mitigation technologies, and a mass of relatively small and poor countries with a very low production of green patents and a vast range of green specialization profiles, which are however related to the greening of more traditional domains and sector (railways, oil, soil and water).
Moreover, our study confirms that most countries' green specialization patterns tend to be constant over time and that leaders tend to be specialized in technologies that are still integrated in the old technological regime, with no change in the technological paradigm.

Keywords: sustainable development, green innovation, machine learning, self-organizing maps
JEL: Q01

1 Introduction

Climate change and the transgression of several ecological boundaries ask for urgent action from industry and economy, whose transformation and reform imply significant costs, which are, however, lower than the costs of inaction or delay. (Stern, 2008) (Acemoglu et al., 2012)
Several scholars identify the response to the current environmental emergency in a deep socio-technical transformation, a socio-technical paradigm change, boosted by effective policies pushing in the direction of a sustainability and green growth. (Freeman, 1992; Perez, 2004, 2010; Altenburg and Pegels, 2012; Mathews, 2013)
This process involves multiple actors (individuals, firms, governments) and layers (local, national, transnational).
Against this backdrop, we focus on countries, since they are the major responsible for promoting and coordinating internal and international actions intended to manage the above-mentioned issues.
In particular, we examine green innovations, which represent one of the most relevant drivers of a socio-technical transformation geared towards sustainability. (Aghion et al., 2009)
Our study builds upon the national system of innovation approach and the sustainability-oriented innovation systems (SoIS) method, which consider (green) innovations as both the engine and the result of complex interactions lead by the national level. (Freeman, 1995; Altenburg and Pegels, 2012)

The aim of this paper is to investigate how OECD and BRICS countries are tackling the environmental challenges, by tracking their green technological profiles through the use of patent data for three years: 1990, 2005 and 2015. Our method consists in an unsupervised machine learning approach, the so-called *Self-Organizing Map* (SOM), which allows to group/cluster countries according to their green technological similarities, providing an insightful technological taxonomy, which is the object of our analysis.

The results reveal a sharp distinction between a small leading group of large and rich countries with a high production of green patents and green specialization in climate change mitigation technologies, and a mass of relatively small and poor countries with a very low production of green patents and a vast array of specializations in their green profile, which are however always related with the greening of more traditional domains and sector (railways, oil, soil and water).
Moreover, our study confirms that most countries' green specialization patterns tend to be constant over time and that leaders tend to be specialized

in technologies that are still integrated in the old technological regime, with no change in the technological paradigm

The rest of the papers is structured as follow.
Section 2 outlines the theoretical framework, where we summarize the most relevant strands of literature on the topic. Section 3 presents the data and technique used for the study. Section 4 shows and discusses the results, while section 5 concludes.

2 Theoretical Framework

The emerging answer to the urgent environmental issues at the world level is the "greening" of economic activities and technologies, with the aim of decoupling economic growth from resource consumption and environment pollution, by replacing resource-intensive and polluting industries and technologies with sustainable ones. (Altenburg and Pegels, 2019)
Some scholars advocate for a new technological and economic paradigm (Freeman, 1992), geared towards sustainable development and clean technologies, which is steered by the so-called *clean tech* revolution. (Pernick and Wilder, 2007)
A techno-economic paradigm consists in 'the set of the most successful and profitable practices in terms of choice of inputs, methods and technologies and in terms of organisational structures, business models and strategies' (Perez, 2010) (p.13). Scholars identify a series of five techno-economic paradigms ranging from the Industrial Revolution to the last present one, "the age of information and telecommunication". (Perez, 2004; Mathews, 2013)
The evolution from one paradigm to another is a long-term societal transformation, which requires extensive innovations and their widespread adoptions and it happens for the contextual modification of both society needs and the underlying technology. (Freeman, 1991) (Perez, 2010)
Milunovich and Rasco (2008) identified in the upcoming *clean tech* revolution a transition towards a *sixth* paradigm, which is partly a fulfilment of the fifth paradigm, based on IT/ITC, but it is also heavy influenced by renewable energies and by a more sustainable mode of production. (Mathews, 2013)
The sixth paradigm should challenge the oil-based fourth techno-economic paradigm, which is responsible for the current carbon lock-in (Unruh, 2000), that the *clean tech* revolution is trying to break. (Mathews, 2013)

Since large techno-economic system transition requires both innovation and a radically new-mode of production Freeman (1996), Aghion et al. (2009)

argues there exist the need of a large public and private investments in innovation, in particular eco-innovation, in order to turn on the so-called 'green innovation machine'. (Aghion et al., 2009)
Aghion et al. (2009), in fact, highlights that the innovation factor cannot be disregarded in any economic model pursuing a sustainable growth pattern. For this reason, the term eco-innovation, defined as the new or modified processes, practices, systems and products which benefit the environment and contribute to environmental sustainability (Rennings, 2000), has become increasingly popular, being at the core of countries' polices, firms' practices and scholars' studies.

The core ideas of these approaches is that for the sixth revolution to take place, the concept of sustainability should be embedded in any innovation system turning any level of the process of innovation in a Sustainability-oriented Innovation Systems (SoIS) (Altenburg and Pegels, 2012). The SoIS consist in a strong governance, able to accelerate the development and deployment of environmentally sustainable technologies, by promoting new types of policies that help to tackle market failures such as externalities and coordination failure (ibid.).

By looking at the challenges ahead, we surmise that the this change of paradigm can take place only at the national level.
In fact, even though "bottom-up" approaches offer fascinating greening patterns and scenarios (Rayner, 2010), they struggle with the fact that, when bottom-up innovation grow beyond its original niche, it often has to adapt to mainstream practices and values losing some or even all of its potency. (Bergman et al., 2010)
Moreover, despite the importance of individual, firm-led and local level initiatives to tackle environmental challenges like climate change, the transnational nature of such defies requires a coordinated national response, which the Paris agreement was the most recent attempt.
Hence, a "top-down" perspective, with countries leading the way, still represents the most credible solution to achieve environmental goals from a policy makers point of view and the best unit of analysis of the issue from a scholar point of view.
Countries, in fact, are responsible for promoting investments and increasingly stringent and coordinated policies able to affect the direction of technological development at industry-level. (Aghion et al., 2009; Altenburg et al., 2017)
Our study goes in the direction of the national system of innovation approach, which describes innovation as the result of a complex interaction of factors at national level. (Malerba, 1993; Chesnais, 1993; Freeman, 1995)

We now provide an overview of the most important strands of literature addressing the eco-innovation issue, putting emphasis on its national dimension. Specifically, we focus on drivers and barriers to eco-innovation as long as the determinant of its diffusion.

A wide strand of the literature has been investigating the factors affecting the development of eco-innovations.
Horbach (2008) and Horbach et al. (2012) have explored the role of regulatory push/pull, technology push and market pull as determinants of eco-innovations, finding that the main motivations for eco-innovation are current and expected regulations, cost savings and customers benefits, along with the improvement of the technological capabilities ("knowledge capital") by R&D.
A conspicuous number of empirical studies focus on the crucial role of regulations in pushing for green innovation. (Hascic et al., 2008; Horbach, 2008; Horbach et al., 2012; Horbach, 2016)
The first theoretical intuition dates back to Porter and Van der Linde (1995), who hypothesized, in the "weak" version of the so-called "Porter hypothesis", that well-designed environmental regulations could spur technological innovation. This hypothesis has been empirically backed by several studies, as reported in Lanoie et al. (2011); Ambec et al. (2013).

While most of the studies on the drivers of eco-innovation takes a firm-level perspective, such as Horbach (2008) and Horbach et al. (2012), there are some which adopt a country-level approach, with Hascic et al. (2008) being the first to look at these issues using a panel of countries.

The second main strand of literature pinpoints the barriers to eco-innovation, which are the so-called "dual externality" issue and the so-called "carbon lock-in". (Lybecker and Lohse, 2015; Unruh, 2000)

The "dual externality" issue works as follows. (Lybecker and Lohse, 2015)
First, environmental pollution involves a negative externality as its social costs may exceed the private costs it entails. Hence, polluters face few market incentives to develop greener technologies as society collectively bears the cost of pollution.
Second, the knowledge required for the development of green technologies can have the characteristics of a public good, i.e. non-excludability and non-rivalry. This means that actors can neither be excluded from accessing and using the good, nor can its use by one actor reduce its availability to any

other actor.
Hence, knowledge leakages during green technologies development, also reduces the incentive for private sector innovation and for the sharing of new and existing technologies and know-how with others. (Lybecker and Lohse, 2015)
The "dual externality" issue represents a major hurdle to eco-innovation, which can be addressed by countries by promoting regulations to reduce negative externalities (fiscal incentives to produce EST) and encourage and protect the production of green technological knowledge (patent system).

The second greatest barrier to eco-innovation is represented by the so-called "carbon lock-in", a notion introduced by Unruh (2000).
Seto et al. (2016) identify three types of "carbon lock-in", which actually co-evolve and mutually reinforce each others: technological, institutional and behavioural.
In fact, the "carbon lock-in" is defined as a process of technological, institutional and behavioural co-evolution, driven by path-dependent increasing returns to scale, which creates persistent market and policy failures, inhibiting the development and diffusion of carbon-saving technologies despite their environmental and economic advantages. (Unruh, 2000; Cecere et al., 2014; Seto et al., 2016)
The bedrock of the "carbon lock-in" is represented by the existence of the *path dependency*, a phenomenon which leads actors promoting or using dirty technologies in the past, to find more profitable to keep investing in dirty techs, instead of "going green".

The third main strand of literature addresses the determinants of eco-innovation diffusion, which represent another important element for our study, since for the purpose of a paradigm transition, eco-innovation should be quickly adopted and diffuse in the society. (Perez, 2010).
Dechezleprêtre et al. (2013) find that the main factors hindering the diffusion of climate-friendly technologies are the following: lax Intellectual property regimes, restrictions on international trade, foreign direct investment and local technological capabilities.
Once again, it emerges that the role of national policies is of paramount importance and, furthermore, Dechezleprêtre et al. (2015) highlights the importance of environmental regulation even in the cross-border diffusion of new technology, while Verdolini and Bosetti (2017) focus on the impact of domestic environmental policies on the inward technology transfer of cleaner innovation from abroad, finding that environmental policy contributes to attracting foreign cleaner technology options, depending on the nature of the im-

plemented policy instruments. In particular, market-based approaches positively impact technology transfer to both OECD and non-OECD economies, while non-market based approaches have at best only a weak effect in OECD countries. (Verdolini and Bosetti, 2017)

All in all, the national level plays a key role in pushing for the disruption of the technological "Business as Usual" and the promotion of a progressively green growth, through green industrial policies.
Green industrial policies, in fact, aim at accelerating the structural transformation towards low-carbon, resource-efficient economy, in ways that also enable productivity improvements. (Altenburg et al., 2017).
This may end in diverging national technological trajectories, reflecting societal preferences, factors endowments, power constellation and policy frameworks. (Altenburg and Pegels, 2012)
In fact, some countries, because of their institutional choices, along with their economic development and industrial policies, are "early movers" in the field of the green economy, pioneering several types of green technologies.
For example, most of the OECD countries are forerunner in the production and adoption of EST, with about 90% of green technologies originating in OECD countries. (OECD, 2017)
On the other side, there are the so-called "latecomers", those countries, which are lagging behind in the promotion of a sustainable development and which are now facing the trade-off between 'greening now' or 'cleaning up later'. (Altenburg and Pegels, 2019)
This trade-off is particularly true and strong for a special group of countries, the so-called BRICS (Brazil, China, India, Russia and South Africa), which have to manage fast rates of economic growth and serious environmental challenges. These countries are providing different answers to the "sustainability challenge", as highlighted by Kılkış (2016).

The aim of this paper is to investigate how OECD and BRICS countries are tackling the environmental challenge, by tracking their evolution in terms of green technological over the time period between 1990 and 2015.
Our primary objective is to cluster countries by their green technological output, in order to outline their green technological profile, by observing their green techs quantity and specialization.
Lastly, we compare the positioning and the evolution of the countries in the clusters with respect to their green technological profile in order to identify possible common patterns at technological level.
In order to do so, we focus on patenting activities in green technology, using OECD data on green patents. (OECD, 2016)

In particular, we focus on a specific set of technologies, that are those intended to the "climate change mitigation", since they are considered the main drivers of the technological paradigm change/shift, which we suppose is underway.

As far as the methodology is concerned, most of the economic literature is build around the concept of hypotheses testing and econometrics as the tool to perform the analysis. (Varian, 2014)
However, economics of innovation has a long standing tradition in the use of taxonomy, the classification of observations, to organize an otherwise chaotic bulk of information.
Notable example is the Pavitt's taxonomy, which groups sectors according to their source of knowledge for the inventive activity. (Pavitt, 1984)
Another interesting example is offered by Malerba and Orsenigo (1996), whose sectoral patterns of innovation base differences in the innovative quality on properties of the technology. Source of inspiration is also Ergas (1987), which groups countries according to the type on innovation policy.

Thus, this paper is an attempt to map the pattern of green inventive activity by using an unsupervised machine learning approach, in order to provide a useful technological taxonomy for OECD and BRICS countries based on their environmental patents. Furthermore, by analyzing the emerging taxonomy, we try to verify whether a new technological paradigm geared towards climate mitigation solutions is in the making.

3 Data & Empirical Strategy

Our study employs OECD-based data and an unsupervised machine learning approach, based on the Self-Organizing Map technique (SOM), of which we provide a description in the next paragraphs.

As far as data are concerned, we employ patent data, which are not only used a valid proxy for eco-innovation (Haščič and Migotto, 2015), they are also considered a factor that can spur the development of environmental-sound technologies (ESTs), by addressing the negative externality that arises from the imperfect appropriability of knowledge. (Lybecker and Lohse, 2015)

3.1 The datasets

The dataset is composed by data retrieved from the section of the OECD iLibrary devoted to the environment-related technological patents by country. (OECD iLIbrary, 2019)
The dataset counts 46 technological variables (45 categories of environmental technological patents plus the total number of 'green' patents) for 41 countries (36 OECD countries + 5 BRICS countries) over 3 years (1990, 2005, 2015).
Table 5.1 offers an overview of the environmental technologies encompassed by this study, with their IPC class. The list is based on OECD (2016), which identifies a selection of environmental-related technologies, divided in three main areas:

- environmental management
- water-related adaptation
- climate change mitigation

OECD (2016) contains a broader list of technologies, encompassing +100 categories and subcategories of environmental-related patents, from which we choose a selection of 45 macro-categories of environmental technological patents in the 3 main areas, in order to help the algorithm to perform a meaningful clustering based on these selected inputs.

Our study also uses data on GDP, GDP per capita, population and CO2 per capita, which are retrieved from OECD online archives. (OECD, 2019)

3.2 Pattern recognition and SOM

Traditionally, the taxonomic approach to epistemology, that is to create a partition of empirical observations based on their characteristics, has been carried on by a careful qualitative evaluation of data made by the researcher. In the words of most philosophers of science, classification is a mean to 'bring related items together' (Wynar et al., 1985, p. 317), "putting together like things' (Richardson, 1935) (Svenonius, 2000, p. 10), 'putting together things that are alike' (Vickery, 1975, p. 1) (see Mai (2011) for a review).
Of course, the antecedent of this dates back in the Aristotelian positive approach to science, which describes and compare *vis á vis* the Plato's normative approach (Reale, 1985).
More recently, the availability of large data-set made a qualitative approach to the creation of taxonomic possible only at the expense of a sharp a-priori reduction of the information in data.
However, at the same time algorithm and computational power allow for an automatic elaboration of the information with the purpose of creating a taxonomic. This approach is known as pattern recognition, unsupervised machine learning or clustering and has been introduced in science by the anthropologists Driver and Kroeber (1932) and the pyschologists Zubin (1938) and Tyron (1939).
Typically, unsupervised algorithm are fed by rich data-sets in term of both variables and observation and require as main output the number of groups to be identified from the researcher. On this basis as output, they provide a classification which minimize within-group variation and maximize between-groups variation, usually captured by some measures of distance in the n-dimensional space of the n variables.
Although among these methods in social science the use of K-means algorithm MacQueen et al. (1967) is the most widespread, it has some weaknesses such as a possible dependence by initial condition and the risk of lock-in in local optima. More recently, the *Self-Organized Maps* (SOM) (Kohonen, 1990) gained attention as a new method in pattern recognition since they improves on K-means and present other advantages such as a clear visualization of the results.
SOM are based on artificial neural networks and consist in algorithm that allows to explore datasets and a creating spatially organized internal representations of the various features of input signals (Kohonen, 1990). The results of this self-organization process are different types of maps, which allows to capture similarities and complementary among the elements used as input. The *Self-Organizing Map* (SOM) has advantages for information extraction (i.e., without prior knowledge) and the efficiency of presentation

(i.e., visualization), which make it suitable in several disciplines, from ecological sciences (Chon, 2011) (Mostafa, 2010) to economics (Carlei and Nuccio, 2014) (Nuccio et al., 2019).
Since algorithms of pattern recognition's process information without any a-priori hypothesis, the educated ex-post evaluation of the output is a crucial phase in the application of unsupervised modelling and, for this reason, an easy visualization became pivotal.
Here, we do not present the details of the algorithm since they are easy to access in other works, but we rather guide the reader in the interpretation of the results. Specifically, we employs SOM to cluster OECD and BRICS countries based on series of features which capture their green technological endowments overtime, proxied by the number of patents.

4 Results

4.1 Clusters description and interpretation

The SOM input consists of 46 (45+1) variables summarized in table 5.1, which describes the technological green profile of the country.
Since the SOM make use of an Euclidean distance in the 46-dimensional space, we scale and center all the variables to make this operational meaningful. The observations represent 41 countries (36 OECD and 5 BRICS) described in 3 years (1990, 2005, 2015) for a total of 123 country-year observations.

As a further input of the algorithm, we define the topology of the output that is in this case a $3X3$ grid, for a total of nine groups [1].
Figure 4.1 on the left shows the 9 clusters and the distributions of the observations. Please recall, that the SOM output is not only a simple partition of the observations, but also a projection of the between-clusters distance on a 2-dimensional surface in which neighbours clusters are more similar to each other than with other distant ones.
Figure 4.1 on the right shows the distance between clusters: for instance the upper right cluster 9 is isolated from the neighbour clusters, while the two blue clusters in the bottom-right corner are very similar.

[1] the number of groups in the classification is arbitrary and depends on the research question. There exist algorithms which suggest an optimal number of clusters based on information measure, but the educated guess of the researcher is usually the best choice (Carlei and Nuccio, 2014) (Ambrosino et al., 2018)

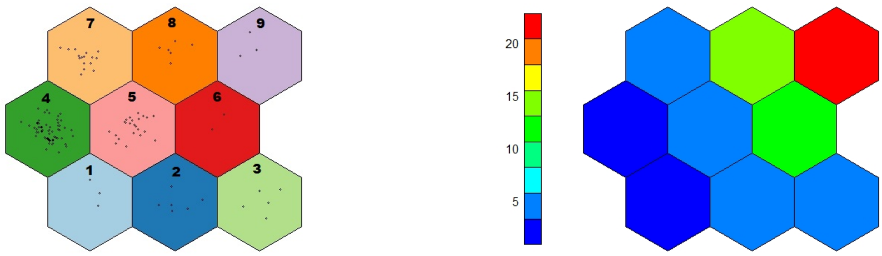


Figure 4.1: Clusters (left) and Neighborhod distance (right)

An unsupervised exercise requires the ex-post educated interpretation of the clusters.
To do that, we characterize clusters with some additional variables of interests, which were not included as SOM input and help clusters' description. Figure 4.2 shows the clusters' average values for all these variables: total number of green patents, GDP, GDP per capita, population and CO2 emission per capita.
Moreover, we provide information about clusters' green technological profile, captured by the number of green patents in each technological category and shown by figure 4.3 and clusters' green specialization, measured as *Revealed Technological Advantage* [2] and shown by figure 4.4 .
Table 4.1 summarizes the clusters' features, with the first two columns specifying for each cluster the three most prominent technologies for its characterization and the three less important ones, according to the SOM input.

By looking at the above-mentioned figures, we see that Cluster 9, which includes only U.S. and South Korea in recent years (see table 4.2), clearly stands up as the most green one along any dimension of green technological classes together with Cluster 8 which always follows as the second. Cluster 8 groups Germany, Japan and China. The proximity on the map does not come as a surprise since in the SOM grid similar clusters are neighbors.
Cluster 8 and 9 are also the clusters with the highest average of both total green patents and GDP per capita. Cluster 9, despite grouping rich countries with a high intensity of green technology, it is also the one with the largest emission per capita in C02.

[2] $RTA_{ij} = \frac{n/\sum n_{ij}}{\sum\limits_{j} n_{ij}/\sum\limits_{i}\sum\limits_{j} n_{ij}}$, where n is the number of green patents

Along this dimension also the neighbor cluster 6 show a very high level of emission. Cluster 6 groups only countries from cluster 8 and 9 in previous decades. Cluster 6 together with cluster 3 is also the only cluster with strong orientation towards nuclear energy.
At the opposite side of the map, cluster 1 and 2 (Finland, Canada, Italy and UK) are characterized by high GDP per capita, a high green patents intensity and a lower emission per capita than cluster 8 and 9. Similarly to cluster 9, cluster 1 and 2 are characterized by a specialization in carbon capture and storage technologies.
The remaining clusters are not characterized by any clear vocation.
All in all, this description captures the distinction between a leading group of large and rich countries with a high production of green patents and a mass of relatively small and poor countries with a very low production of green patents . Germany, Japan, U.S. and Korea are the leader in the production of green technologies. France and China dominate the nuclear energy, while UK, Canada, and Italy stay behind nevertheless the good performance.

The picture is much more scattered if we analyze the specialization profile, which is measured with the Revealed Technological Advantage index and shown by figure 4.4.
France and China co-evolved towards a specialization in nuclear energy and in technology related to the processing of minerals.
Cluster 8 and 9 are specialized in all technologies related to climate mitigation and environmental monitoring, while all the other clusters show a vast array of specialization profiles in their green profile, but always related with the greening of more traditional areas (rail, oil, soil and water).

The picture sketched by these data does not rest a case for the evolution towards a sixth revolution or a change of paradigm.
In fact, even cluster 9 which is developing most of the green technology is mostly focus on on carbon capture and storage (CCS) technology, which represent an advanced and sophisticated solution for the mitigation climate change, but yet integrated in the fossil fuel based technological regime.
In fact, CCS technology involves capturing the CO2 produced during fossil-fuel combustion and storing it in underground geologic reservoirs instead of emitting it into the atmosphere'. (Stephens, 2006) CCS is certainly a technology capable of delivering significant emissions reductions from the use of fossil fuels in power generation and industrial applications and when combined with bioenergy, CCS can also remove CO2 from the atmosphere and generate "negative emissions" (a potentially critical option for limiting future temperature increases to 2C or below). (MIT-EDU, 2019)

However, CCS technologies are not really new, since projects injecting CO2 for enhanced oil recovery (EOR) have been operating in the United States since the early 1970s, while the Sleipner CCS Project in Norway [3] has marked its 20th year of operation in 2016. (MIT-EDU, 2019)
But what is more important from our qualitative view point, CCS do not help breaking world's fossil fuel dependence, as they act as an end-of-pipe solution part of the dominant technological regime.

To conclude, we would like to underline the absence of a cluster of countries with a strong vocation in renewable energy generation or energy efficient technologies, which could be considered a technological leader in the fight to tackle the climate change challenge and in the pursue of the technological paradigm change.

Given the features and the characterization of the clusters, in the next paragraph we investigate the composition of the clusters, by looking at the countries inside them and their evolution over time.

[3] Sleipner was the world's first commercial CO2 storage project, which was built in Norway in order to evade the 1991 Norwegian CO2 tax. (MIT-EDU, 2019)

Figure 4.2: SOM features

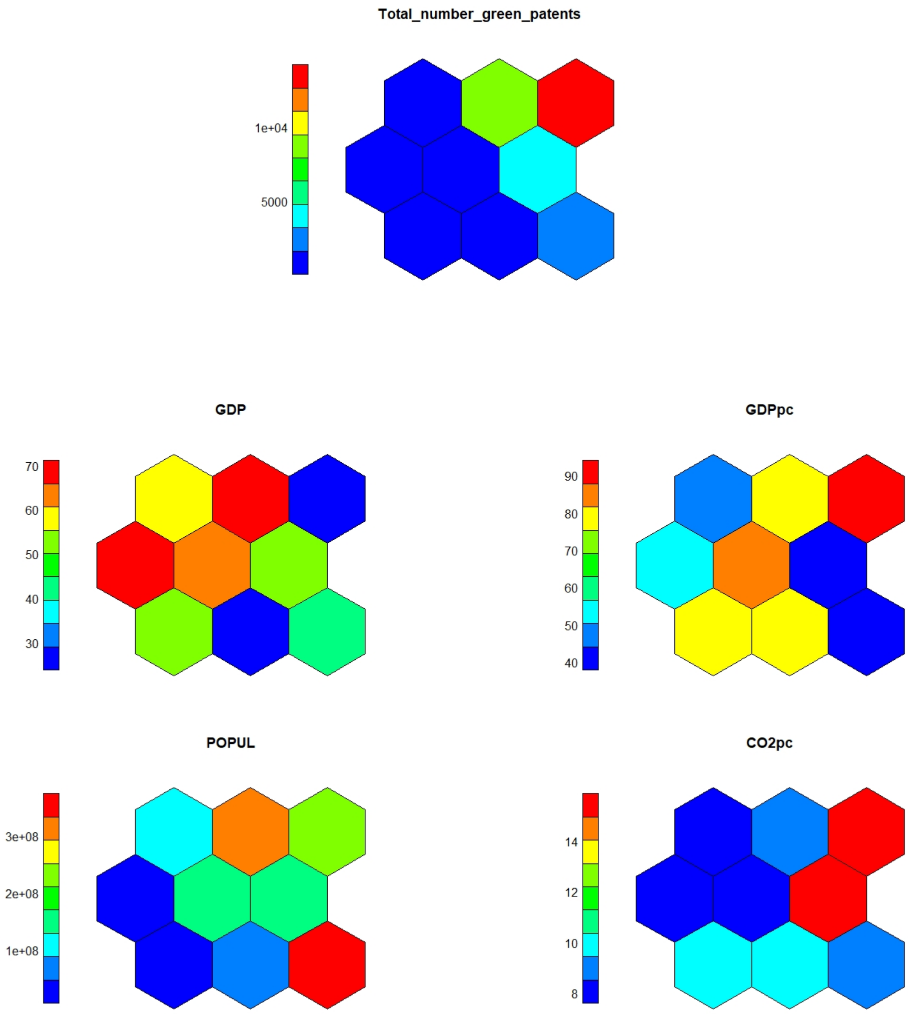
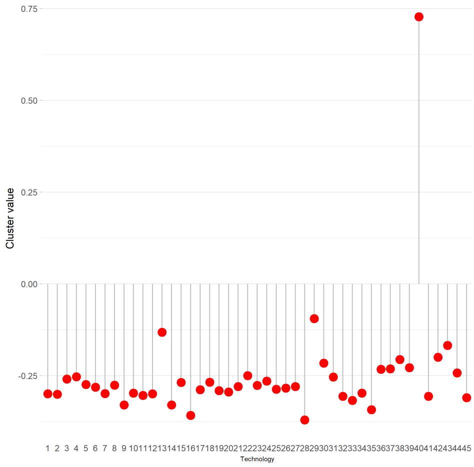
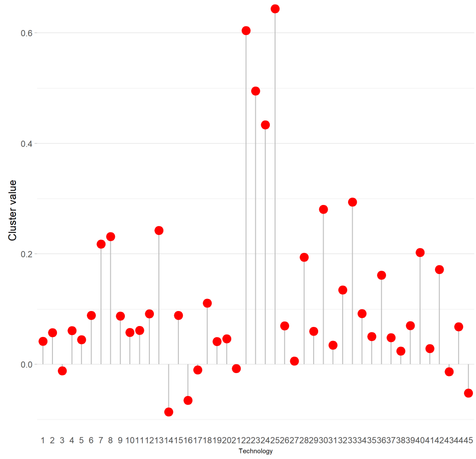


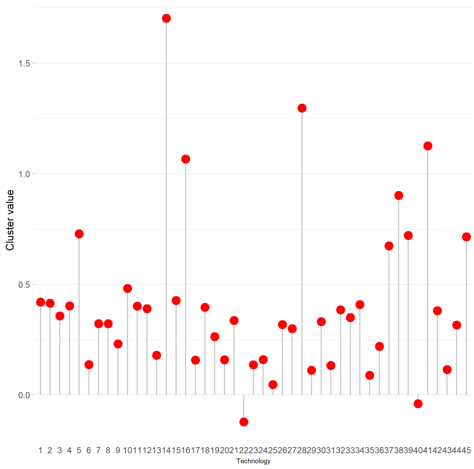
Figure 4.3: Cluster Technological Profile



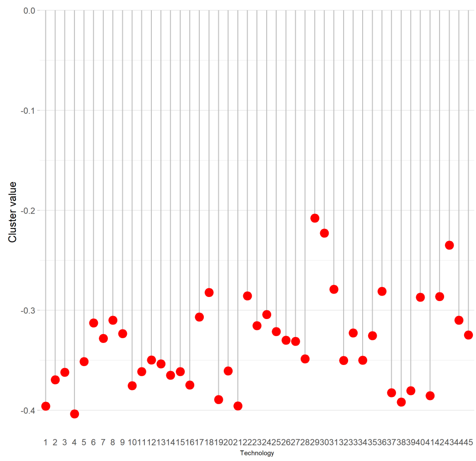
(a) Cluster 1



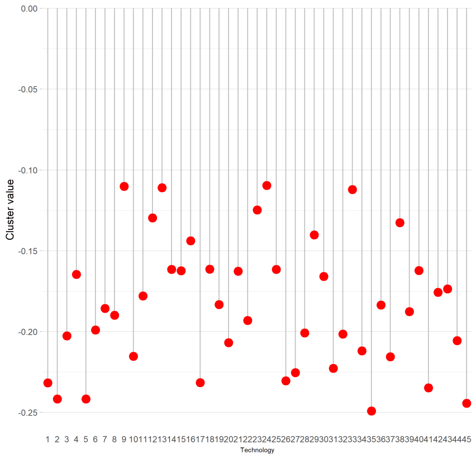
(b) Cluster 2



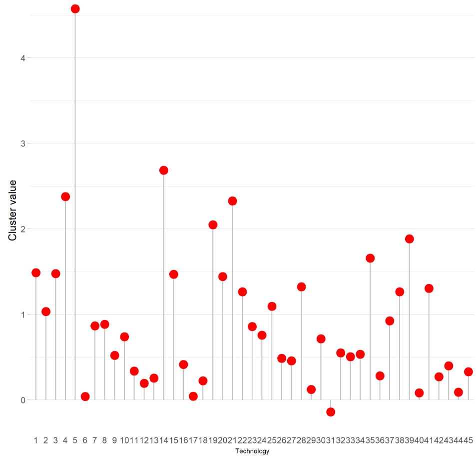
(c) Cluster 3



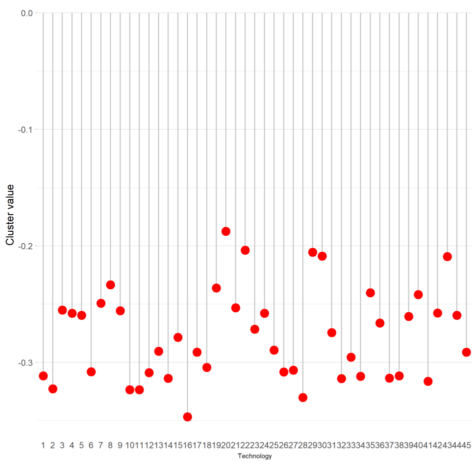
(d) Cluster 4



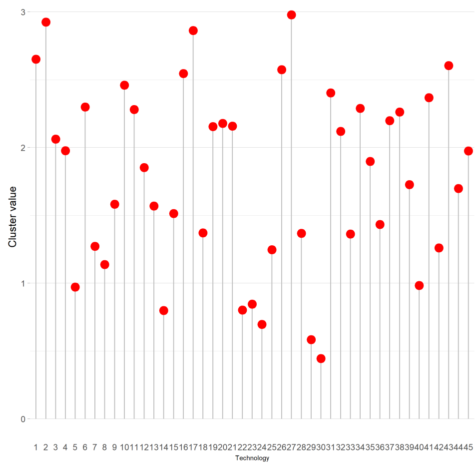
(e) Cluster 5



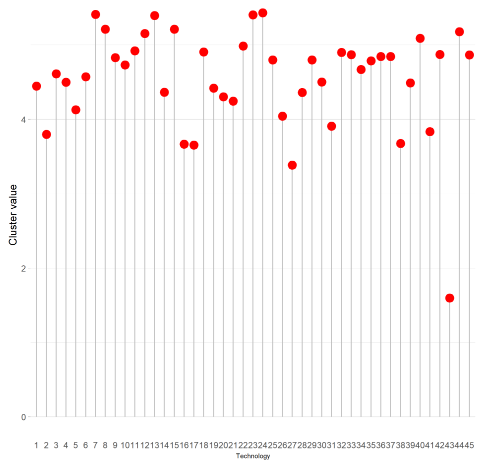
(f) Cluster 6



(g) Cluster 7

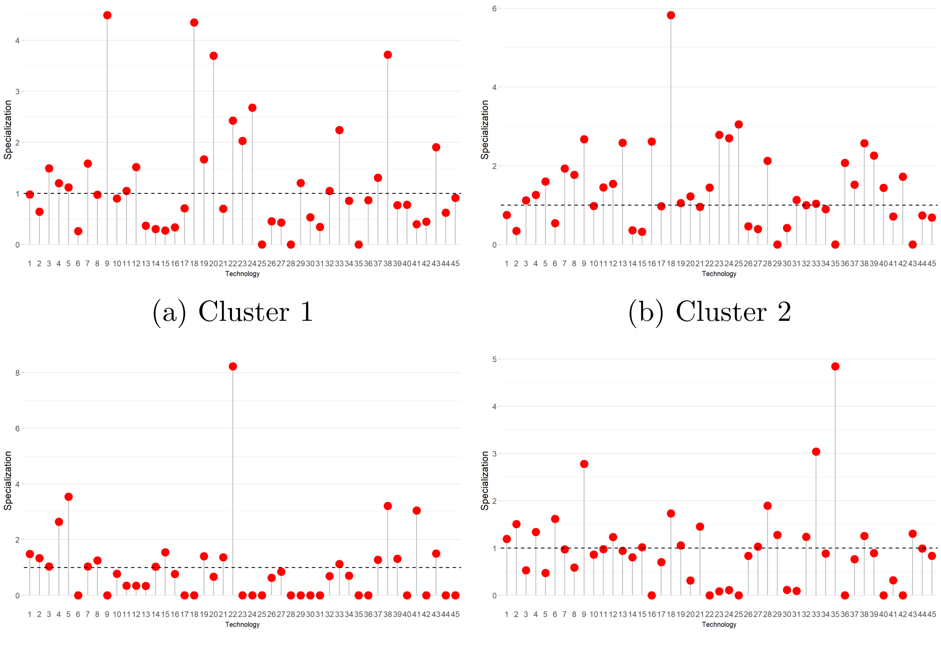


(h) Cluster 8



(i) Cluster 9

Figure 4.4: Cluster Specialization Profile

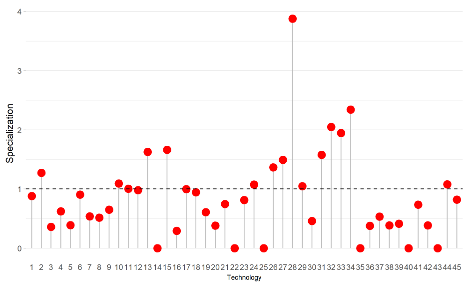


(a) Cluster 1

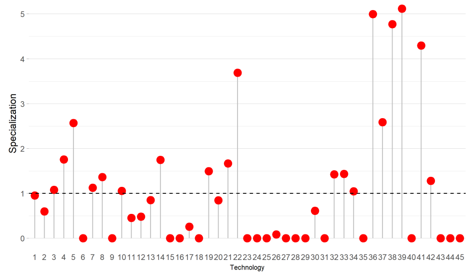
(b) Cluster 2

(c) Cluster 3

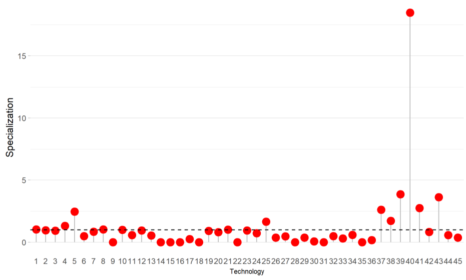
(d) Cluster 4



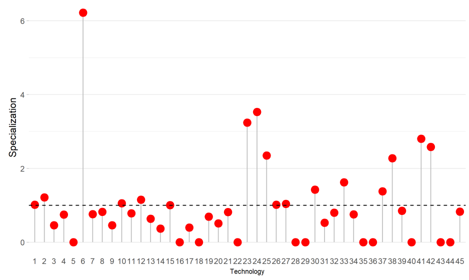
(e) Cluster 5



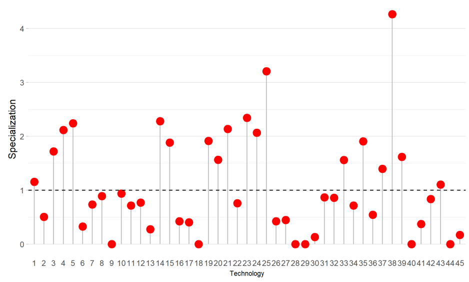
(f) Cluster 6



(g) Cluster 7



(h) Còuster 8



(i) Cluster 9

Table 4.1: Clusters characteristics: technologies, GDP pc, Population, CO2 pc and % BRICS

SOM	Most relevant techs	Less relevant techs	GDP PC	POPULATION	CO2 EMISSION PC	% BRICS
1	Technologies related to oil refining and petrochemical industry Maritime or waterways transport Energy generation from fuels non fossil origin	Rail transport Efficient electrical power generation/transmission/distribution Architectural or constructional elements improving the thermal performance of buildings	medium/high	very low	low/medium	0%
2	Capture or disposal of greenhouse gases Other than CO2 Enabling techs for GHG emissions mitigation (potential) Capture storage sequestration disposal of GHG	Nuclear energy Efficient electrical power generation/transmission/distribution Enabling techs for GHG emissions mitigation (potential)	medium/high	low	low/medium	0%
3	Nuclear energy Rail transport Technologies for the processing of minerals	Enabling techs for GHG emissions mitigation Techs for oil refining and petrochemical industry Capture or disposal of greenhouse gases Other than CO2	very low	very high	low	20%
4	Maritime or waterways transport Air transport Production/process final industrial/consumer products	Waste management Environmental management Solid waste management	low	very low	very low	10%
5	CO2 capture or storage (CCS) Supply side technologies -water availability- Energy generation from fuels of non fossil origin	Elements improving the thermal performance of buildings Enabling techs for GHG emissions mitigation (potential) Soil remediation	high	medium	very low	17%
6	Soil remediation Nuclear energy Waste management	Enabling technologies in transport Environmental Monitoring Enabling technologies in the energy sector	very low	medium	very high	0%
7	Wastewater treatment Enabling for GHG emissions mitigation (potential) Maritime or waterways transport	Efficient electrical power generation/ transmission/distribution Rail transport Climate change mitigation techs	low	low/medium	very low	6%
8	Road transport Air pollution abatement Enabling technologies in the energy sector	Air transport Maritime or waterways transport CO2 capture or storage (CCS)	medium/high	high	low	17%
9	CO2 capture or storage (CCS) Water related adaptation technologies Capture/storage/sequestration/disposal of GHG	Production/process final industrial/consumer products Road transport Enabling technologies in the energy sector	very high	medium	very high	0%

4.2 Countries' evolution

In this section we intend to analyze countries' evolution across the clusters over time, in order to understand the technological dynamics occurred over the period considered.
By inspecting table 4.2, which summarizes the cluster attribution of each country, we observe that:

- in 1990, the most populated cluster is cluster 4, with 26 countries, including 3 BRICS countries (Brazil, India and South Africa), followed by cluster 7, with 10 countries (all OECD countries)
- in 2005, the most populated cluster is cluster 4, with 18 countries, including 2 BRICS (Brazil and South Africa), followed by cluster 5, with 8 countries (all OECD)
- in 2015, the most populated cluster is cluster 4, with 18 countries, including 1 BRICS country (South Africa), followed by cluster 5, with 11 countries, including 2 BRICS (Brazil and India)

We notice that not only a large group of countries belongs to cluster 4 in every time periods, but that the very same countries belonging to cluster 4 in 1990 keep belonging to cluster 4 also in 2005 and 2015.
This means that a considerable number of countries shows a persistent vocation for green technologies related to maritime and waterways transport, air transport and production and process of final industrial or consumers goods, which are the most prominent technologies of cluster 4.
The persistent vocation in these sectors can be explained by the fact that these sectors are characterized by a relatively slow innovation pattern (in aviation see Lee and Mo (2011)), fueled by an incremental type of innovation, which is less costly and favours a long-term commitment to the development of technologies in these fields.
By cross-checking table 4.2 and figure 4.2, we learn that countries of cluster 4 are relatively small countries (low population), with low GDP per capita (with exception of Luxembourg), but high GDP (they are all OECD, but South Africa). We find that these countries' features can be related to the type of innovation (incremental) that is most common in the technological sectors, which countries of cluster 4 are characterized by.
The other countries follow peculiar patterns of evolution over time.
Among the OECD countries, we observe some countries moving from one cluster to another between 1990 and 2005, where they remain also after 10 years. This means that after a change in their green technological vocation, they show a persistent vocation in specific green sectors.

This kind of pattern is followed by Germany (cluster 6 in 1990, then cluster 8 in 2005 and 2015), Japan (cluster 3 in 1990, then cluster 8 in 2005 and 2015) and USA (cluster 6 in 19990, then in cluster 9 in 2005 and 2015).
In particular, Germany and Japan show a persistent vocation in green technologies related to road transport from 2005 onward, while USA are characterized by technologies devoted to the carbon capture and storage (CCS) of GHG.
These green vocation can be clearly attributed to Germany and Japan's long tradition in automotive sector and USA's consolidated know-how in oil sector (CCS is a technology originally employed during fossil fuels extraction).
We also observe that France and China have moved together from cluster 5 (vocation in water supply and carbon capture and storage) in 1990 to cluster 3 in 2015 (vocation in nuclear energy and processing of minerals). Among BRICS countries, we observe South Africa maintaining the same green technological vocation over time (cluster 4 in 1990, 2005 and 2015), while the other BRICS are less constant in their green technological vocation.
In fact, we see Brazil starting in cluster 4 (1990 and 2005) and ending up in cluster 5 (2015), while Russia starting in cluster 5 (1990) and ending up in cluster 3 (2005 and 2015).
China follows an even more peculiar technological patterns, since it shifts from cluster 5 (1990), to cluster 8 (2005), ending up in cluster 3 (2015).
Similarly, India moves from cluster 4 (1990) to cluster 7 (2005), to reach cluster 5 (2015).
This means that a part from South Africa, BRICS countries are still not characterized by peculiar and specific green technologies (at least not until 2015).

Figure 4.5 shows the evolution of the countries across the clusters between 1990 and 2015.

We conclude by highlighting that the clustering exercise we performed has represented and mirrored quite well the real technological evolution of the countries over the time period considered.
In fact, if we focus, for example, on Germany, we find that its move from cluster 3 (vocation in green technologies related to nuclear energy, rail transport and process of minerals) to cluster 8 (vocation in green technologies related to road transport, air pollution abatement and energy sector) consistently represents the historical evolution of the country's green technological vocation.
In fact, in the 90s Germany is characterized by a consolidated nuclear energy sector, a long-standing industrial tradition in the process of minerals (mining activities in the Ruhr region) and a rail transport sector in expansion thanks

to the "fall of the wall" in 1989; these national features are consistent with the most prominent green technologies highlighted by the SOM for Germany in 1990.
Germany has also a long-standing technological tradition in the automotive sector, which starts to turn green in the early 2000s, mostly due to the introduction and progressive tightening of national and European cars and air regulations.
Tightened environmental regulations are also the trigger of the development of air pollution abatement technologies and technological advancements in the energy sector, that are the other two fields where Germany show a vocation in 2005 and 2015 in, according to the SOM analysis.
Moreover, if we look at the specialization of clusters 3 and 8 we also find that Germany has a persistent specialization in transport technologies.
Looking at the BRICS, Brazil's SOM-based vocation in fuels of non fossil origin in 2015 mirrors Brazil's technological commitment to agrofuels, which is a forerunner of.
SOM also reveals that Brazil is characterized by technologies in sectors such as maritime and waterways, rail transport and production/process of final goods in 1990, while CO2 capture and storage and water availability technologies in 2005 and 2015.
This shows that our SOM analysis based on patents data does not simply confirm well-know technological vocations and specializations, but also provides new pieces of information about the country's technological vocation and specialization.

Finally, we would like to underline that there can be some discrepancies between the SOM-based technological vocation and specialization and the actual countries' technological endowments; this can be due to the fact that our study relies on patents, which are a good proxy for innovation development, but a weak one for innovation adoption and deployment.
Therefore, there are some countries which lag or lack in terms of green innovation development, but they are advanced in terms of green technologies adoption and deployment, which would require other types of proxy to be captured (e.g. number of green technologies installed).
This is the case of Netherlands or Denmark, whose longstanding tradition in renewable energy technologies, which have been widely adopted on their territory, does not emerge from our patent-based study.
On the whole, our study offers a reliable technological taxonomy based on SOM-generated clusters and an interesting picture of countries green technological evolution, which blaze the trail to further investigations on world green innovation patterns.

Figure 4.5: Evolution of countries green profile from 1990 to 2015

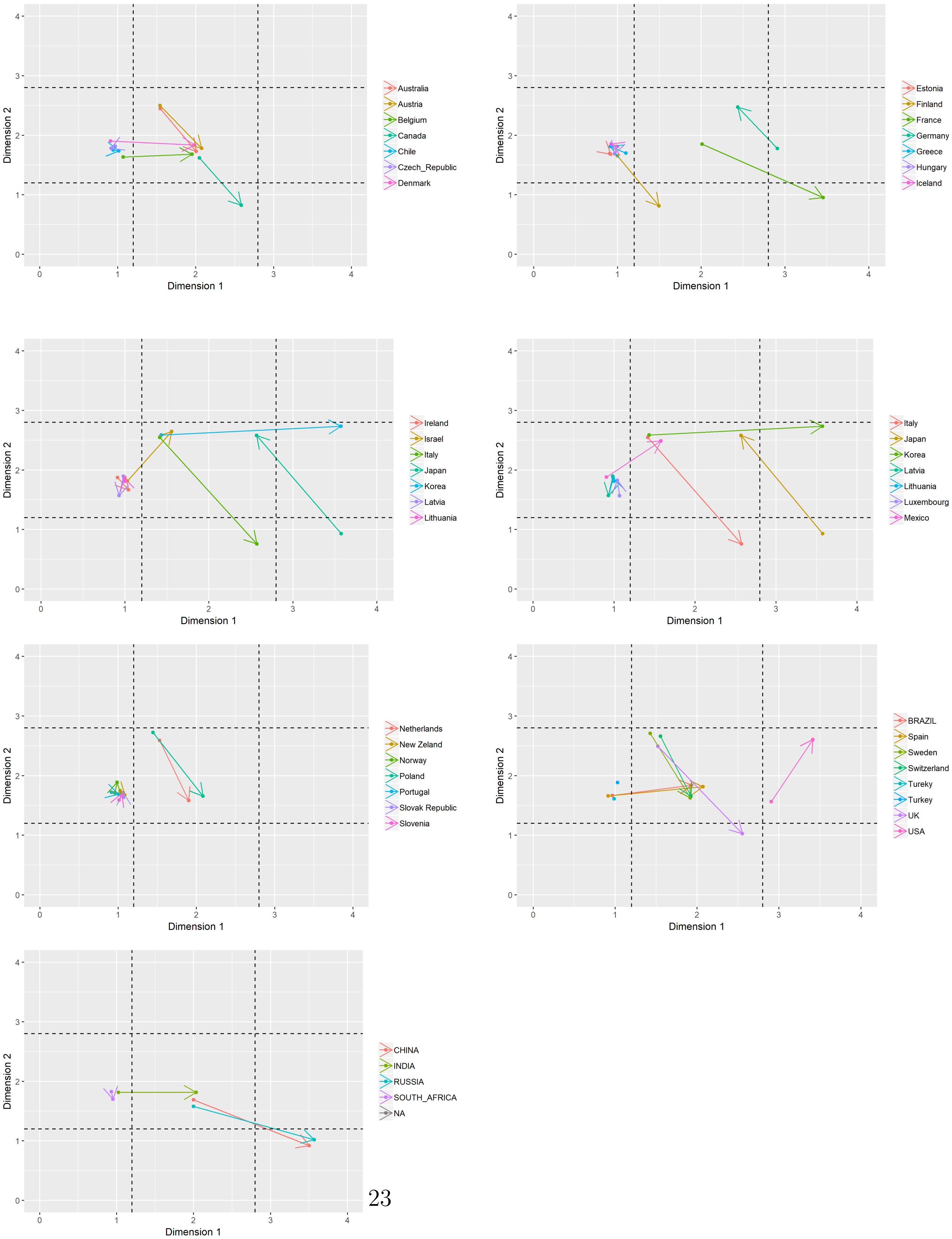


Table 4.2: Countries within the clusters over time

Cluster	**Countries**		
	1990	**2005**	**2015**
SOM 1		Belgium, Finland	Finland
SOM 2		Canada, France UK	Canada, Italy UK
SOM 3	Japan	Russia	France, China Russia
SOM 4	Belgium, Chile Czech, Denmark Estonia, Finland Greece, Hungary Iceland, Ireland Israel, Latvia Lithuania, Luxembourg Mexico, New Zealand Norway, Portugal Slovak, Slovenia Spain, Turkey Brazil, India South Africa	Chile, Estonia Greece, Hungary Iceland, Ireland Latvia, Lithuania Luxembourg, Mexico New Zealand, Portugal Slovak, Slovenia Turkey, Brazil South Africa	Chile, Czech Estonia, Greece Hungary, Iceland Ireland, Latvia Lithuania, Luxembourg New Zealand, Norway Portugal, Slovak Slovenia, Turkey South Africa
SOM 5	Canada, France China, Russia	Australia, Austria Denmark, Italy Netherlands, Spain Sweden, Switzerland	Australia, Austria Belgium, Denmark Netherlands, Poland Spain, Sweden Switzerland, Brazil India
SOM 6	Germany, USA		
SOM 7	Australia, Austria Italy, Korea Netherlands, Poland Sweden, Switzerland UK	Czech, Israel Norway, Poland India	Israel, Mexico
SOM 8		Germany, Japan Korea, China	Germany, Japan
SOM 9		USA	Korea, USA

4.3 Technological evolution and paradigm change

In this section we conclude our reasoned analysis of the technological evolution occurred in the time period considered, pursuing the goal of evaluating whether countries are moving and pushing towards the technological paradigm change identified by several scholars. (Freeman, 1992; Perez, 2004, 2010; Pernick and Wilder, 2007; Milunovich and Rasco, 2008; Mathews, 2013)

First, we highlight the presence of a conspicuous group of countries with a persistent green specialization in technologies aimed at tackling climate change in transports, with focus on maritime, waterways and air transport, and in the production and process of final goods (countries in cluster 4).
This means that, since from 1990, a relevant group of countries, which are characterized by low population, low GDP per capita, but high GDP (see figures **??**), have been developing technologies contributing to the reduction of anthropic impact on climate of relevant sectors (air and maritime transport are among the most polluting sectors, as well as production of final goods) and this trend has endured over time.
This trend could imply that small countries with low GDP per capita have set off in a pathway towards the adoption of a more sustainable technological paradigm, even though a more insightful analysis of the types of innovation involved (incremental vs radical) would be advisable in order to reach better conclusions.
Moreover, as shown by figures 4.2, countries in cluster 4 have a low level of total green patents, which can be an indicator of a slow-paced transition towards green technologies.
On the other hand, countries with the highest level of green patents production (countries in cluster 9), that are USA (2005, 2015) and Korea (2015) (see figure 4.2 and table 4.2), show a vocation in carbon capture and storage (CCS) technologies, which implies that a large share of their green inventive activity is devoted to the development of this kind of technologies.
In spite of the fact that CCS are included among the technologies intended to the climate change mitigation (OECD, 2016), CCS represent technologies that are complementary to those aimed at the energy production using fossil fuels, which incarnate the fossil fuel-based technological paradigm.
In fact, CCS technology involves capturing the CO2 produced during fossil-fuel combustion and storing it in underground geologic reservoirs instead of emitting it into the atmosphere. (Stephens, 2006)
Moreover, countries with the second highest level of total green patents (countries in cluster 8), that are Germany (2005, 2015), Japan (2005, 2015) and China (2005), show a green vocation in road transport, pollution abatement

and enabling technologies for energy, which are sectors characterized not only by radical types of innovation, but also and often by incremental and modular types of innovation (e.g. refinements of the ICE, end-of-pipe solutions). (Aghion et al., 2016)
This implies that their green vocation is oriented towards innovations that are not much disruptive with respect to the incumbent technology, but that can be part of the dominant technological regime.

Therefore, we conclude that there is a current transition toward more sustainable technological solutions, but countries that are leading the way in terms of green patents productivity are specialized in technologies that are still integrated in the old technological regime. Hence, based on these data, we are not facing a technological paradigm change.

5 Conclusion

The world is being challenged by an increasing number of environmental defies (climate change, natural resources depletion, pollution), which ask for an urgent answer from the countries, in terms of new economic paradigm, innovative technological trajectories and bold policy choices.
The aim of this paper is to investigate how OECD and BRICS countries are tackling the environmental challenge, by tracking their green technological profile over time.
Our research is based on an unsupervised machine learning approach, which consists in the use of an algorithm to group countries according to their 'green' technological similarities.
By running the so-called *Self-Organizing-Map* (SOM) algorithm on data about 46 technological variables (45 categories of environmental technological patents plus the total number of green patent) over 41 countries (36 OECD countries + 5 BRICS countries) for 3 years (1990, 2005, 2015), we obtain 9 clusters of countries, each of which has a specific green specialization, alias green technological profile. We also use data on countries features, such as GDP, GDP per capita and CO2 per capita, in order to better characterize clusters.
The analysis of the clusters highlights that there is a quantitative distinction between a leading group of large and rich countries (Germany, Japan, U.S. and Korea) with a high production of green patents and a mass of small and relatively poor countries with a very low production of green patents.
The picture is much more scattered if we analyze the specialization profile.
It emerges that clusters 8 and 9 are characterized by technologies related to climate mitigation and environmental monitoring, while all the other clusters show a vast array of specialization profiles in their green profile, but always related with the greening of more traditional areas (rail, buildings, soil and water).
By analyzing countries' technological evolution inside the clusters, our SOM-based study substantially confirms the real technological evolution experienced by the countries, whose green specialization tends to show constant patterns over time, apart from those of BRICS, which display rather variable patterns of specialization over time.
Finally, the picture sketched by these data does not rest a case for the evolution towards a sixth revolution or a change of paradigm. In fact, even cluster 9, which is developing most of the green technology, is mostly focused on carbon capture and storage (CCS) technology, which represent an advanced and sophisticated solution for the mitigation climate change, but yet integrated in the fossil fuel based technological regime.

Hence, we conclude that, based on these data, we capture the presence of a transition toward more sustainable technological solutions, but we are not facing a drastic change in the technological paradigm.

As many other empirical investigations, also this one presents some caveats to be mentioned.
First, in order to obtain meaningful results from the algorithm, our study does not include all 141 green technological categories, as in the dataset from OECD (2016).
This prevent us from performing a more grain-refined research on the type of countries' green specialization. However, wider technological classes allow a better grasp of countries' technological trends.
Second, we analyze patents, which are good proxy for innovation development, but a weak one in terms of innovation adoption and deployment.
Therefore, there can be some discrepancies between the SOM-based technological specializations and the actual countries' technological endowments, due to the fact that there are some countries lag or lack in terms of green innovation development, while they are advanced in terms of green technologies adoption and deployment, which would require other types of proxy to be captured (e.g. number of green technologies installed).
This is the case of Netherlands or Denmark, whose long-standing tradition in renewable energy technologies, which have been widely adopted on their territory, does not emerge from our patent-based study.

Our study intends to contribute to the literature of economics of innovation by providing a kind of technological taxonomy thanks to a clustering exercise. However, our study could offer interesting sparks also for an analysis oriented towards the geography of innovation. (Breschi and Malerba, 2001)
We conclude by hoping that this study can encourage further investigations on the answers provided by the "socio-techno-institutional complex" to the environmental challenge, by means of classical econometric methods as well as innovative research tools.

Table 5.1: Technological types with their corresponding IPC class

Type of Technology	IPC Class
1. ENVIRONMENTAL MANAGEMENT	**various**
1.1 AIR POLLUTION ABATEMENT	various
1.2 WATER POLLUTION ABATEMENT	various
1.3 WASTE MANAGEMENT	various
1.4 SOIL REMEDIATION	B09C
1.5 ENVIRONMENTAL MONITORING	F01N11, G08B21/12-14
2. WATER-RELATED ADAPTATION	**various**
2.1 DEMAND-SIDE TECHNOLOGIES (water conservation)	various
2.2 SUPPLY-SIDE TECHNOLOGIES (water availability)	various
3. CLIMATE CHANGE MITIGATION	**various**
3.1 CLIMATE CHANGE MITIGATION RELATED TO ENERGY (generation, transmission of distribution)	**Y02E**
3.1.1 RENEWABLE ENERGY GENERATION	Y02E10
3.1.2 ENERGY GENERATION FROM FUELS OF NON-FOSSIL ORIGIN	Y02E50
3.1.3 COMBUSTION TECHS WITH MITIGATION POTENTIAL (e.g. using fossil fuels, biomass, waste, etc.)	Y02E20
3.1.4 NUCLEAR ENERGY	Y02E30
3.1.5 EFFICIENT ELECTRICAL POWER GENERATION, TRANSMISSION OR DISTRIBUTION	Y02E40
3.1.6 ENABLING TECHNOLOGIES Technologies with potential or indirect contribution to emissions mitigation	Y02E60
3.1.7 OTHER ENERGY CONVERSION OR MANAGEMENT SYSTEMS REDUCING GHG EMISSIONS	Y02E70
3.2 CAPTURE, STORAGE, SEQUESTRATION OR DISPOSAL OF GREENHOUSE GASES	**Y02C**
3.2.1 CO2 CAPTURE OR STORAGE (CCS)	Y02C10
3.2.2 CAPTURE OR DISPOSAL OF GREENHOUSE GASES OTHER THAN CO2	Y02C20

Type of Technology	IPC Class
3.3 CLIMATE CHANGE MITIGATION RELATED TO TRANSPORTATION	**Y02T**
3.3.1 ROAD TRANSPORT	Y02T10
3.3.2 RAIL TRANSPORT	Y02T30
3.3.3 AIR TRANSPORT	Y02T50
3.3.4 MARITIME OR WATERWAYS TRANSPORT	Y02T70
3.3.5 ENABLING TECHNOLOGIES IN TRANSPORT	Y02T90
3.4 CLIMATE CHANGE MITIGATION RELATED TO BUILDINGS	**Y02B**
3.4.1 INTEGRATION OF RENEWABLE ENERGY SOURCES	Y02B10
3.4.2 ENERGY EFFICIENCY IN BUILDINGS	various
3.4.3 ARCHITECTURAL OR CONSTRUCTIONAL ELEMENTS IMPROVING THERMAL PERFORMANCE OF BUILDINGS	Y02B80
3.4.4 ENABLING TECHNOLOGIES IN BUILDINGS	Y02B90
3.5. CLIMATE CHANGE MITIGATION RELATED TO WASTEWATER TREATM. / WASTE MANAGEMENT	**Y02W**
3.5.1 WASTEWATER TREATMENT	Y02W10
3.5.2 SOLID WASTE MANAGEMENT	Y02W30
3.5.3 ENABLING TECHNOLOGIES WITH A POTENTIAL OR INDIRECT CONTRIBUTION TO GHG MITIGATION (e.g. bio-packaging)	Y02W90
3.6 CLIMATE CHANGE MITIGATION RELATED TO THE PRODUCTION OR PROCESSING OF GOODS	**Y02P**
3.6.1 TECHNOLOGIES RELATED TO METAL PROCESSING	Y02P10
3.6.2 TECHNOLOGIES RELATING TO CHEMICAL INDUSTRY	Y02P20
3.6.3 TECHNOLOGIES RELATING TO OIL REFINING AND PETROCHEMICAL INDUSTRY	Y02P30
3.6.4 TECHNOLOGIES RELATING TO THE PROCESSING OF MINERALS	Y02P40
3.6.5 TECHNOLOGIES RELATING TO AGRICULTURE LIVESTOCK OR AGRO-ALIMENTARY INDUSTRIES	Y02P60
3.6.6 TECHNOLOGIES IN THE PRODUCTION PROCESS FOR FINAL INDUSTRIAL OR CONSUMER PRODUCTS	Y02P70
3.6.7 CLIMATE CHANGE MITIGATION for SECTOR-WIDE APPLICATIONS	Y02P80
3.6.8 ENABLING TECHNOLOGIES WITH A POTENTIAL CONTRIBUTION TO GHG EMISSIONS MITIGATION	Y02P90
TOTAL GREEN PATENTS	all

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Essay 3.
Smart cities and sustainable mobility: the effect of a smart and sustainable mobility policy on urban air quality in Paris region

Abstract

As urban air pollution continues to reach warning levels and an increasing number of urban areas embrace the "smart city" paradigm, sustainable mobility gains a central role for cities to become "green" and truly "smart".
Paris, as one of the leading world smart cities, is engaged in the promotion of global and local commitments to sustainability, including an ambitious package of mobility policies, which are transforming the city in a laboratory of a new kind of urban mobility.
The paper aims at investigating the impact of a Paris' innovative sustainable urban mobility policy, the electric car- sharing service *Autolib*, on air quality in Paris region.
In order to detect a possible variation of urban air pollution trends due to the introduction of this service, we use a "Difference in Difference" model, whose application is partially backed by a preliminary graphical analysis.
The empirical results shows that *Autolib* has had a negative and statistically significant impact on PM10, the most representative urban air pollutant, corresponding to a greater than 12% cut of the average level of the pollutant.
Similar results are found for other 2 key urban air pollutants: NOx and NO2.
Some robustness checks, based on the use of alternative pollutant indicators, provide further support to the study.
These findings suggest that the availability of the electric car-sharing service in Paris region has contributed to induce a shift in transport modes, reducing the number of circulating private cars, thus cutting the emissions and the concentrations of key urban pollutants, with benefits for the environment and human health.

Keywords: environmental sustainability, smart mobility, policy evaluation
JEL: O30, Q55

1 Introduction

Traffic and its pollution represent a huge issue for cities and metropolitan centers, since they affect urban air quality (environmental effects) and the quality of life of citizens and cities' visitors (health effects).

The transport sector is responsible for a large proportion of urban air pollution. (WHO, 2019)
In particular, transport is a significant and growing contributor to particulate air pollution; in fact, road transport is estimated to be responsible for up to 30% of particulate emissions (PM) in European cities and up to 50% of PM emissions in OECD countries. (WHO, 2019)
Besides particulates, namely PM10 and PM2.5, other relevant transport-related air pollutants are ground-level ozone (O3), nitrogen oxides (NOx), nitrogen dioxides (NO2), carbon monoxide (CO), together with carbon dioxide (CO2) and methane (CH4), which are strong greenhouse gases. (WHO, 2019)
The adverse effects on health of the air pollutants have been deeply investigated (Krzyżanowski et al., 2005), with several short-term and long-term studies revealing that exposure to air pollutants, such as airborne particulate matter and ozone, is associated with increases in mortality and hospital admissions due to respiratory and cardiovascular disease. (Brunekreef and Holgate, 2002)
Moreover, the scientific uncertainty about the presence of a threshold concentration, below which no effects on health are likely, makes the exposure to such pollutants more dangerous, even at low levels. (Brunekreef and Holgate, 2002)

Paris and its big surrounding metropolitan area suffer from systematic traffic-borne air pollution and its related human health impacts.
Despite a declining trend of some key air pollutants during the period 2007-2017, the concentrations keeps being problematic for most of the pollutants (AirParif, 2019) and the health consequences are serious.
In fact, among 100 major urban areas worldwide, Paris has ranked 27th in population and 17th in the number of deaths attributable to transportation emissions in 2015, meaning that the health burden from transportation emissions in Paris is disproportionately heavy. (Anenberg et al., 2019)
As a result, Paris has had the ninth-highest fraction of deaths from air pollution attributable to transportation emissions in 2015, being among the ten

worst cities worldwide. (Anenberg et al., 2019) [1]

On the other hand, Paris is engaged to become a smart and sustainable city, with the current administration promoting and supporting several local plans and international commitments, aimed at tackling the most urgent urban environmental issues, among which, the transport-related air pollution emergency gains a primary role.
With the aim of pursuing a smart and sustainable mobility, Paris city is developing and implementing a series of innovative policies, devoted to address the environmental externalities of the mobility.
First of all, the city has recently started to gradually ban diesel vehicles (2016), in order to totally phase them out by 2024.
Moreover, the officials responsible for the urban transport policy are planning a complete exit from combustion engine vehicles, or fossil-energy vehicles, by 2030.
Besides these "command and control" measures, the city is also involved in the creation and extension of pedestrian areas, 20km/h & 30 km/h zones, which represent "soft" interventions, yet giving a significant contribution to the lowering of polluting emissions.
Among the "soft and smart" policies adopted by the city to promote sustainable mobility solutions, there is the deployment and diffusion of an electric-car sharing service, the so-called *Autolib*, which has been introduced, first in Europe and worldwide, in 2011.

The aim of the paper is to investigate the impact of this "soft and smart" policy, that is the introduction of the electric car-sharing service *Autolib* in Paris region, on a selection of air quality indicators (PM10, NOx and NO2)[2].
By using environmental data from *AirParif* and data retrieved from *Autolib* and local administrative websites, we apply a *Difference in Difference* estimation model to examine the variation of air pollution trends in treated and untreated zones of Paris region, after the introduction of the *Autolib* service, while controlling for other relevant mobility policies and factors.
By doing so, the study finds that *Autolib* is an effective instrument, able to reduce the annual average pollution of 3 key air pollutants, namely PM10, NOx and NO2, which results to diminish respectively by 10%, 12% and 27%, with respect to their average.

[1]The ten cities are, in order, Milan, Rotterdam, Turin, Stuttgart, Mexico City, Leeds, Manchester, London, Paris, and Cologne. (Anenberg et al., 2019)

[2]Some investigations have been carried out also on PM2.5 and Tropospheric Ozone (O3), but lack of data prevented from conducting any reliable empirical analysis with these indicators

These results have relevant policy implications, since they show that the promotion of a soft and smart mobility policy, taking the form of the introduction of an innovative sustainable mobility service, namely Autolib, is proved to be beneficial for the environment, helping to pursue urban sustainability.
This makes advisable to support such measures, which encourage the voluntary use of sustainable means of transport, in order to achieve urban environmental and health quality goals.

The rest of the paper is structured as follows.
Section 2 outlines the theoretical framework, introducing the concept of externalities related to urban mobility, their evaluation methods, the types of policy intervention available to tackle them and some study-cases evaluating mobility policy effectiveness.
Section 3 present the mobility policy examined and the hypothesis of the current study, while section 4 and 5 describe respectively data and the empirical model, through which test the above-mentioned hypothesis.
Section 6 shows and discusses results, while section 7 provides some robustness check and section 8 concludes.

2 Theoretical framework

2.1 Road transports & externalities

Road transports, especially automobile-related transports in urban areas, produce negative externalities, which consist in the social costs of transports, occurring when the marginal external costs of transport born by the whole urban community exceed private costs of transportation. (Calthrop and Proost, 1998)
The main externalities produced by car transportation are congestion, accidents, noise, local air pollutants and greenhouse gases, with the last two elements representing the so-called *environmental externalities* of transportation.
Foster (1974) actually identifies 13 specific local forms of adverse environmental effects due to urban transport alone, among which, air pollution plays a key role.
The main transport-generated air pollutants affecting urban areas are Particulate Matter with a dimension equal to/below 10 micron and Particulate Matter with dimension equal to/below 2.5 micron, which originate from the combustion process of the internal combustion engines and the use of wheels and blacktop by cars.
Further significant air pollutants are represented by Nitrogen Oxides and Nitrogen Dioxide, which are mainly originated from fuel combustion.
They are both precursors of Tropospheric or "ground-level" Ozone, another relevant transport-related air pollutant, which is known to be a key factor in chronic respiratory diseases, such as asthma, and also to damage ecosystem structures and functions. (WHO, 2019)

2.2 Environmental externalities & the internalization issue

Transports' environmental externalities basically leads to *market failure* in providing environmentally harmless transportation, since transport users, in particular private car users, do not have the incentives to fully bear all the costs of their chosen mode of transport.
In fact, road transports deal with resources which are public, such as clean air, which is an example of perfect public good (non-excludable and non-rival) or quasi-public, such roads, which represents a congestible good (excludable, but partially non-rival). (Perman et al., 2003)
As a consequence, the purely market-based management of transports tends

to be inefficient and under-optimal, since each transport's consumers is unwilling or unable to bear the full costs of a car-oriented transportation mode. This causes a need for policy intervention and internalization instruments, in order to fully take into account the environmental costs of transport.
However, also an institutional transport management can fall into failure, the so-called *regulation failure*, which is due to the fact that institutional manipulation of transport provision often does not take fully into account environmental costs. (Button, 1990)

2.3 Environmental externalities & policy interventions

We now examine the main regulatory instruments that policy makers have in their tool kit in order to manage transport environmental externalities.
There are three different routes to tackle transport's environmental externalities: assignment of property rights, pollution taxes or eco-friendly subsidies, and the so-called "command and control" measures.
The solution of the assignment of property rights represent the classical *Coase approach*, which is used when the environmental externalities are caused by the absence of markets and it consists in the bargaining between the parties and the production of an efficient level of the externality.
With this approach, pollution production becomes efficient since the marginal value of additional production to the polluter equals the marginal dis-benefit to the affected party. (Button, 1990)
An example of practical solution based on the *Coase approach* is represented by the so-called "cap-and-trade" systems, used to regulate environmental externalities in the energy sector.
The main shortcomings of the *Coase approach* are associated with non-excludability of the public goods, the high transaction costs and the free riders incentives, which make the efficient bargaining unlikely.
An effective and efficient bargaining is also made difficult by the presence of a bargaining asymmetry between transport users, who form clearly identifiable groups and possible lobbies and those affected by environmental degradation, who are dispersed and also belonging to future generations.
The solution to this issue can be represented by the transfer of resources from the wider population to transport sector, by funding large scale investments for road transports and redesigning of urban areas.
A different approach to address environmental externalities is the one proposed by Pigou, which consists in imposing taxes or promoting subsidies, with the aim of aligning the private cost and demand functions, so that they reflect the full social costs and benefits.

Fullerton and West (2000) highlights that, despite individual car's emissions cannot be measured reliably enough to impose a Pigouvian tax, a second-best combination of taxes (on gas, size, vintage) and subsidies (to buy small cars or to scrap the old ones) can help achieving welfare improvements from a zero-tax scenario.
Congestion charges are also an example of taxes imposed at urban level, in order to try to make car-users pay the full cost of their day trips to the city centres.
The main shortcomings of the so-called *Pigouvian approach* are represented by the fact that this approach is informationally demanding and it faces possible regulatory failure in its implementation. (Button, 1990)
In fact, since the size and the scope of taxes and subsidies are determined by governments, and because of their imperfect knowledge of the market, the outcome is likely to be inefficient.

Both the Coase and the Pigouvian approaches belong to the so-called "incentive-based" economic instruments aimed at addressing and correcting the problem of transport externalities. (Santos et al., 2010)
The alternative set of economic instruments is represented by the so-called "command-and-control" measures, which involve the specification of standards for environmentally adverse activities, such as technological standards, emission or fuel standards.
Also this solution is informationally demanding and faces the possibility of regulatory failure.

There exist also a further category of instruments, the so-called "soft solutions", consisting in sustainable and smart mobility measures, such as car-sharing, electric-car-sharing services, bike-sharing and electric bike sharing, which are offered by the policy-makers to provide alternative options to usual transport modes.
These solutions, along with bike lanes and low speed streets can be considered part of the large-scale investments aimed at reshape urban mobility and geography. (Croci and Rossi, 2014)
All the above-mentioned instruments can be used separately or together, but their implementation is being increasingly necessary to effectively tackle the problem of transport externalities.

2.4 Urban transport policy evaluation

Policy evaluation is a crucial part of the transport management and several studies have been carried out to evaluate the effectiveness of the main urban transport policies.
The literature on transport policy evaluation divides in two main strands: one examining the policy impact on urban welfare, the other focusing on policy impact on urban environmental quality.
On the welfare side, Proost and Van Dender (2001) discovers that regulation of emission technology and of fuel efficiency does not lead to welfare gains, while transport pricing policies yield substantial gains for the urban areas.
More recently, Mayer and Trevien (2017), evaluates the impact of the extension of urban rail transport in Paris on its employment and population growth, finding that the opening of new regional rail stations caused a significant rise in employment in the municipalities connected to the network, while it did not produce any effect on overall population growth.
On the environmental side, Safonov et al. (1999) provides an intriguing simulation study predicting urban mobility impacts on urban air quality in Brussels Capital region, based on two possible policy scenarios.
The first scenario, the so-called "Business as Usual" one, entailing no introduction of any sustainable mobility policy in the region, outlines a growth of traffic and fuel consumption with a subsequent increase of the CO2 and PM emissions.
The second scenario, the so-called "voluntarist" one, entailing the introduction of a series of measures and policies aimed at reducing private cars traffic in the region, forecasts a substantial decrease of traffic, fuel consumption and emissions (CO2, PM, SO2).
Davis (2008) offers an interesting econometric insight of the effect of the introduction of driving restrictions on air quality in Mexico City.
The study, in fact, estimates the environmental impact of the introduction of the urban traffic program "Hoy No Circula", based on an alternate number plate system, finding no evidence that the driving restrictions have improved air quality, which on the contrary experienced a worsening due to a "rebound effect".

Besides Davis (2008), there has been almost no relevant econometric study investigating the impact of specific urban mobility policies on urban air quality.
The present paper aims at filling this gap in the literature, being the first one to provide a preliminary econometric appraisal of the impact of an electric car-sharing service on urban air quality.

3 Hypothesis development

Paris city, together with its surrounding municipalities, has been the first European and world city to introduce in 2011 a private-public electrical car-sharing service, which has registered an increasing number of users and has been active under the name *Autolib*, until August 2018.
Hence, this paper comes timely to evaluate the impact of this service on Paris air quality, since the service's main goal was to promote the shift from the use of private polluting cars to the employment of shared clean vehicles, reducing the number of circulating polluting vehicles and the traffic-borne polluting emissions.

Here below, the hypothesis that the paper aims to test.

Hypothesis 1 *The impact of Autolib on PM10*
The first hypothesis of the paper aims at investigating whether the introduction of the electric car-sharing service *Autolib*, a "soft" sustainable mobility policy, has had an impact on air quality in the area of Paris/Ile de France, causing a reduction specifically of PM10 levels.

Hypothesis 2 *The impact of Autolib on NOx*
The second hypothesis of the paper aims at investigating whether the introduction of the electric car-sharing service *Autolib*, a "soft" sustainable mobility policy, has had an impact on air quality in the area of Paris/Ile de France, causing a reduction specifically of NOx levels.

Hypothesis 3 *The impact of Autolib on NO2*
The third hypothesis of the paper aims at investigating whether the introduction of the electric car-sharing service *Autolib*, a "soft" sustainable mobility policy, has had an impact on air quality in the area of Paris/Ile de France, causing a reduction specifically of NO2 levels .

Sections 4 and 5 respectively describe the data and the model of estimation.

4 Data

The present section describes the dataset and the variables used, providing relevant summary statistics and graphical analysis.

4.1 Dataset

Our dataset is the result of the match of three separate data sources: *AirParif*, *Autolib* and *Paris Ma Ville*.
We firstly use data from AirParif (2019), an online dataset with the statistics and trends of the main urban pollutants recorded in the area of Paris, from the early 90s to the current years.
We also use data from *Autolib* website, the official website of Paris electric car-sharing service, providing information on the electric cars and parking stations available within the service in the Paris region.
We also employ data retrieved from *Paris Ma Ville* website and other local agencies web portals, in order to construct the covariates of our study.
The dataset is a panel, composed by 286 observations distributed on 22 selected monitoring stations, taken from 2005 to 2017.

4.2 The variables

4.2.1 Dependent variables

For the dependent variables, we use the following proxies of the urban air quality:

- **Particulate Matter less than 10 micron** (*PM10*),
- **Nitrogen Oxides** (*NOx*),
- **Nitrogen Dioxides** (*NO2*)
- **Tropospheric** or **ground-level Ozone** (*O3*).

Then, we select as relevant indicator for the above-mentioned pollutants their annual average level.
As PM10 indicator, in fact, we use the annual average quantity of PM10, whose limit value is set at 40 $\mu g/\mathrm{m}^3$ and its quality target is set at 30 $\mu g/\mathrm{m}^3$.[3]

[3] according to French and European environmental rules -see AirParif (2019)-

The NOx indicator corresponds to the annual average quantity of NOx, whose maximum annual value is set at 30 $\mu g/\mathrm{m}^3$.[4]
The NO2 indicator corresponds to the annual average quantity of NOx, whose maximum annual value is set at 40 $\mu g/\mathrm{m}^3$.[5]

The pollutants are measured by AirParif monitoring stations, located in different neighborhoods, namely *arrondissments*, of Paris region.
Table 1 shows the list of the monitoring stations and their location, by department and *arrondissment*.
A geographical overview of the Île de France and its department and *arrondissments* is also available at the end of the paper in Figures 3 and 4

4.2.2 Explanatory variable

The independent variable under investigation is represented by *Autolib*, the private-public electric car-sharing service, introduced in the Paris region in 2011.
This variable is a dummy, taking value 1, when the service is working in the *arrondissments* where a AirParif monitoring station is located, and value 0 when it is not.
Table 1 shows the list of the *arrondissments*, where *Autolib* has been activated, with respect to the monitoring stations of *AirParif*.
Autolib is considered active with respect to the *AirParif* monitoring station, if the electric car-sharing service is working in the *arrondissment* where the AirParif station is located.

Data on *Autolib* electric car-sharing stations have been retrieved from the official *Autolib* website.

[4]according to French and European environmental rules -see AirParif (2019)-
[5]according to French and European environmental rules -see AirParif (2019)-

Box 4.1 AUTOLIB': a brief history

Autolib' is an electric car sharing service, which was inaugurated in Paris, in December 2011.

The *Autolib'* system was a follow-up to Paris' successful *Velib'* bike sharing scheme, whose operations began in 2007.

The scheme introduced a fleet of all electric cars, called Bluecars, for public use on a paid subscription basis, employing a citywide network of parking and charging stations.

The system's electric cars were supplied by the Bolloré industrial group, as the result of a collaboration with the Italian automotive firms Cecomp and Pininfarina.

Construction of the Autolib' stations began in mid-2011, and 66 of the scheme's Bolloré Bluecars were deployed for a two-month preliminary trial period between October and December 2011.

The system entered service on 5th December 2011, with an initial fleet of 250 Bluecars and 250 *Autolib'* rental stations serving the city of Paris and 18 surrounding communities (96 in 2016), grouped into the syndicate of associated collectivities "*Autolib'* Métropole".

At the scheme's inception, car availability was a problematic issue, as more Parisians than expected subscribed to the service.

By July 2012, 650 parking and charging stations had been deployed around Paris and the 46 communes participating in the scheme, and by February 2013 there were 4,000 charging points.

The program's user base grew from 6,000 subscribers at the end of December 2011 to 27,000 in July 2012, and reached 37,000 by early October 2012, of which 13,000 had an annual subscription.

By July 2014, *Autolib'* had 2,500 operational vehicles and over 150,000 subscribers, and its cars had covered a cumulative mileage of over 30,000,000 km (19,000,000 mi) since the scheme's introduction.

As of 3 July 2016, 3,980 Bluecars had been registered for the service, and the scheme had more than 126,900 registered subscribers.

In addition to charging its own vehicles, the *Autolib'* scheme has been offering charging services for private owners of electric cars and motorcycles, providing to customers the so-called "recharge" fee option.

On the wave of the success of the Paris experience, in early 2013, the Bolloré Group announced plans to launch a similar car sharing service in Lyon and Bordeaux, but under a different brand name and with no cost to the cities.

In July 2018 the scheme has ceased to operate in Paris, because of the end of the Bolloré contract (and absence of profitability of the service).

The city of Paris, in conjunction with four different mobility operators (Ada, Communauto, Drivy and Ubeeqo), is launching now *Mobilib'*, a car-sharing service, including electric and plug-in hybrid cars.

4.3 Covariates

The first covariate is *Vélib*, the public bike-sharing service, introduced in the Paris region in 2007.
The variable is a dummy, taking value 1, when *Vélib* service is active around the monitoring station, while value 0 when it is not.
As controls, we also use two variables, represented by *20 km/h zones* and *30 km/h zones*, which are two political measures, respectively introduced in 2008 and in several different periods.
They consist in the introduction of urban areas characterised by lower speed-limits for cars, along with pedestrian and bike priority lanes.
The variables take the form of two dummies, taking value 1, when the monitoring station is located within an *arrondissment* where cars cannot exceed 20 km/h or 30 km/h, while they take value 0, when any more stringent speed-limit is enforced in the station's *arrondissment*.
The last covariate is represented by the *traffic restriction zones*, the so-called "Zones à Circulation Reduite", *ZCR*, which consists in a measure, introduced in 2017, aimed at excluding old and polluting vehicles from traffic in certain city areas.
The variable *ZCR* is a dummy, taking value 1, when the station lies within an arrondissment covered by the measure and the policy is enforced, while it takes value 0, when the station is out of the zones interested by the measure or the policy has not been implemented yet.

4.4 Descriptive statistics

4.4.1 Summary statistics

The dataset used in the empirical analysis is a station-level dataset, consisting in 286 station-year observations.

Table 2 provides summary statistics about the dependent variables, which are the environmental indicators measuring the average level of key air pollutants: PM10, NOx and NO2.

INSERT TABLE 2 AROUND HERE

PM10 has an average value of 27.2 $\mu g/\mathrm{m}^3$, which is slightly below the critical value of 30 $\mu g/\mathrm{m}^3$. Nitrogen Oxides have a mean value of 80.77 $\mu g/\mathrm{m}^3$, while the threshold value is set at 30 $\mu g/\mathrm{m}^3$.
Nitrogen Dioxides have a mean value of 38.06 $\mu g/\mathrm{m}^3$, a slightly higher value

than the threshold value set at 30 $\mu g/\mathrm{m}^3$; NO2 also has the highest number of observations (268).

4.4.2 Graphical inspection: parallel trends and absolute trends

We firstly graphically inspect the data on air pollutants to test the parallel trends assumption, which represents the qualitative prerequisite for the application of the Difference in Difference (DinD) model of estimation.
The parallel trend assumption entail that pollutants show a similar, "parallel", trend on average, before the introduction of the policy, between treated and untreated, while a divergent trend on average, after the introduction of the policy, between treated and untreated.
Examining Figure 1, we do not observe the presence of the expected parallel trends for any of the pollutants.
By contrast, Figure 1 show a divergent trend of PM10 between treated (TRUE) and untreated (FALSE) before the introduction of the policy in 2011, while a surprising parallel trend, between treated (TRUE) and untreated (FALSE), after 2011.
Similar pattern evolution shows up also for NOx and NO2.
Hence, the parallel trend assumption graphically fails to hold for each of the pollutants used as proxy for urban air quality.

As a further preliminary test for the Difference in Difference model, we also graphically inspect the absolute trends of the pollutants before and after the introduction of the Autolib service in 2011, in order to verify whether the pollutants show any general pattern before and after the introduction of the treatment in 2011.
Figure 2 shows that some of the pollutants experience a general decline after the introduction of the policy in 2011.
In particular, PM10 displays a declining trend starting right after 2011, as shown by part a) of Figure 2.
On the contrary, Part b) of Figure 2 shows that NOx has a substantially constant pattern before and after the policy implementation.
Part c) of Figure 2 displays that NO2 has a slightly declining absolute trend before the policy implementation and a steeper declining trend right after the year of the policy implementation.
To conclude, our graphical inspection of the absolute trends of the pollutants provides some qualitative support to the implementation of a DinD model.

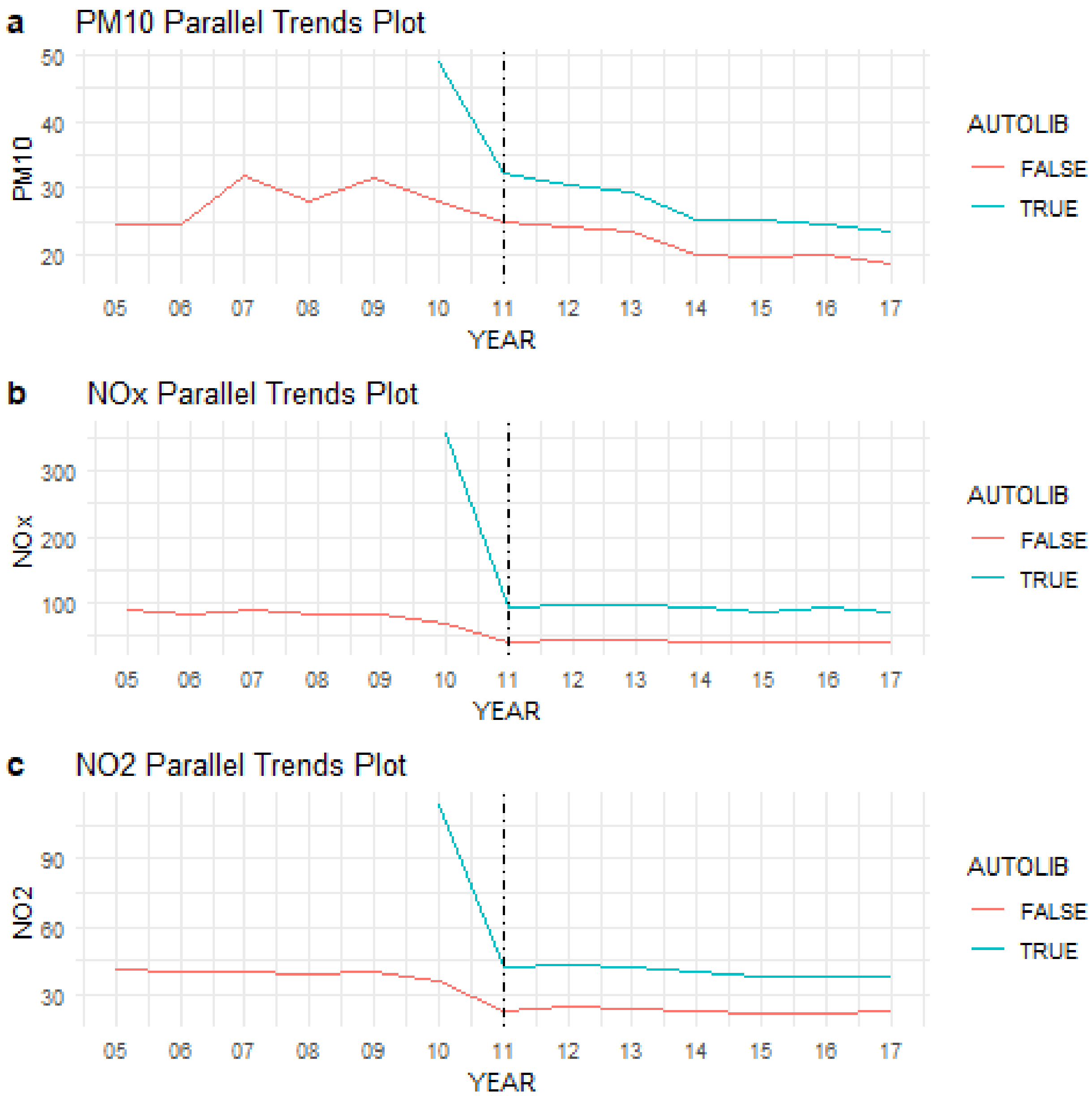

Figure 1: Parallel Trend Plots for PM10, NOX and NO2

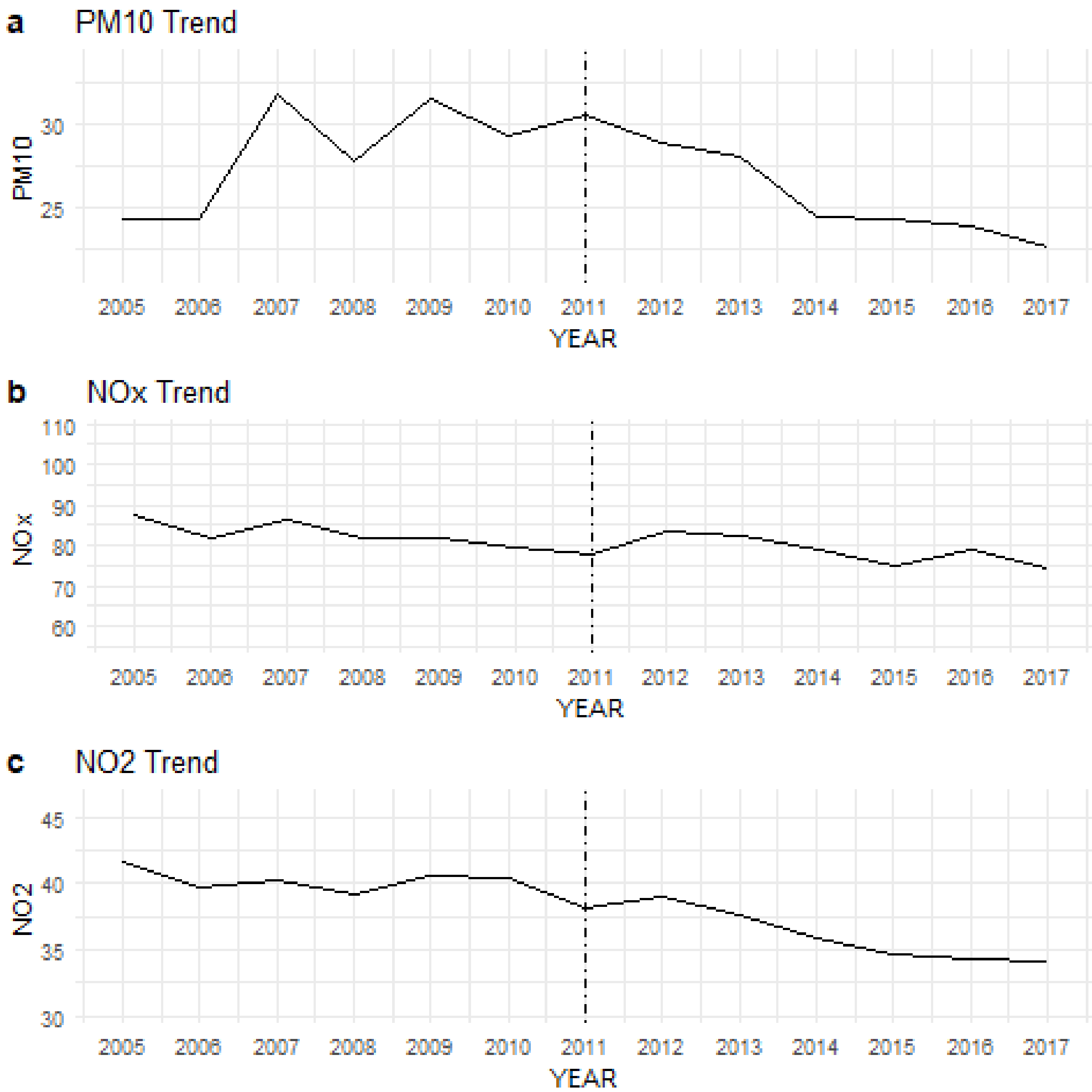

Figure 2: Average annual trends by pollutant

5 Empirical model

The study investigates the impact of the introduction of the electric car-sharing service, *Autolib*, on air quality, which is measured by monitoring stations in some of the most relevant arrondissments of the Paris region. (See Table 1)
We use as dependent variable, the annual average concentration of the following key air pollutants: PM10, PM2.5, NOx, NO2 and O3.
We implement a "Difference in Difference" (DinD) model, which entails taking the difference between the average pollutant trend in the treated stations and the average pollutant trend in the untreated stations, before and after the introduction of the policy measure. We perform the DinD analysis for each type of pollutant.

The DinD model takes the following basic form :

$$PollutAnnAv_{it} = \beta_0 + \beta_1 Post2011 + \beta_2 Policy + \delta_0 Post * Policy + \varepsilon_{it} \quad (1)$$

PollutAnnAv is the annual average level of the pollutant, measured in each of the 22 monitoring stations.
Post2011 correspond to a dummy equal to 1, when the year is 2011 or after 2011 and 0 otherwise.
Policy is a dummy equal to 1, when the *Autolib* service is active and 0 otherwise.
*Post*Policy* is a an interaction term between Post2011 and Policy, taking value 1, when the year is equal or after 2011 and *Autolib* is active, while 0 otherwise.

In order to control for possible annual trends in weather conditions, which could affect pollution trends, we introduce time fixed effects, with the DinD model taking the following form:

$$PollutAnnAv_{it} = \beta_0 + \beta_1 Post2011 + \beta_2 Policy + \delta_0 Post * Policy + \alpha_t + \varepsilon_{it} \quad (2)$$

where α_t is the time fixed term.

We finally control also for station and department fixed effects, producing the following form of the DinD model:

$$PollutAnnAv_{it} = \beta_0 + \beta_1 Post2011 + \beta_2 Policy + \delta_0 Post * Policy + \alpha_t + \gamma_i + \theta_j + \varepsilon_{it} \quad (3)$$

where γ_i stands for the stations fixed term.
where θ_j stands the departments fixed term.

6 Results

The results of the econometric estimations testing Hypothesis 1 are reported in Table 3.

INSERT TABLE 3 AROUND HERE

The first column presents the baseline estimations, testing the impact of Autolib on PM10 annual average concentration, without any control.
The coefficient of the DinD term, the interaction between Autolib and Post 2011, is negative and statistically significant.
In column (2), we show the extended version of the model, which includes additional controls: Vélib, the bike-sharing service, zone20 and zone30, which are zones with pedestrian and bike priority, along with speed-limitations.
The negative and significant effect of Autolib is confirmed also in this setting.
In column (3), we show the results of the model including time controls, finding a persistent negative and significant coefficient of the DiD term.
It means that, even when controlling for possible year-based interference, which can be caused by particular yearly weather or traffic conditions, the effect of Autolib on PM10 still remains and it is negative.
In columns (4) and (5), we further extend the set of control variables, including station (4) and department (5) controls: we keep finding a negative and significant coefficient of the DiD term.
In this final setting, the introduction of Autolib has reduced PM10 average level by 3.367 points, which correspond to a 12% decrease of the pollutant with respect to its average level.

We, then, test Hypothesis 2 and 3, by running additional estimations over NOx and NO2 pollutants, the results of which are reported in Tables 4 and 5.

Column (1) of Table 4, presents the baseline estimations, testing the impact of Autolib on NOx annual average concentration, without any control.
The effect is large (-226.776), negative and statistically significant.
Column (2) of Table 5 shows the results of an extended model, which includes the above-mentioned controls: Velib, the bike-sharing service, zone20 and zone30, which are zones with pedestrians and bikes priority, along with speed-limitations. The Autolib effect is a bit smaller than in the baseline model, but still negative and significant.
Column (3) of Table 5 provides the estimations of the model including time controls, finding a persistent negative and significant coefficient of the DiD term. It means that, even when controlling for possible year-based interference, which can be caused by particular yearly weather or traffic conditions,

the effect of Autolib on NOx still remains and it is negative.
In columns (4) and (5) of table 4, we further extend the set of control variables, including station (4) and department (5) controls: we keep finding a negative and significant coefficient of the DiD term.
In this final setting, the introduction of Autolib has reduced NOx average level by 12.092 points, which correspond to a 15% decrease of the pollutant, with respect to its average level.

INSERT TABLE 4 AROUND HERE

Similarly to the test of Hypothesis 2, we also tested Hypothesis 3, by running DinD estimations of Autolib over NO2 without controls, with controls, with time fixed effects, with station fixed effects and with department fixed effects.
The result stored in Table 5 shows that, also in this case, we always find a negative and statistically significant effect of Autolib over NO2.
We highlight that, within the final setting, including all possible fixed effects, we observe a decrease of the pollutant by 29%, with respect to its average level.

INSERT TABLE 5 AROUND HERE

Overall, the empirical results are substantially in line with our hypothesis and expectations, finding that the introduction of the electric car-sharing service *Autolib* in Paris region has had a negative effect on all the key air pollutants examined.
In fact, it reduces has reduced the average level of PM10, NOx and NO2.

7 Robustness checks

A series of checks are carried out to test the robustness of our results, verifying that the policy examined has had a real impact on urban air pollutants. In particular, we use different indicators for urban pollutants, with the aim of "double checking" the effect produced by the introduction of the electric car-sharing service *Autolib'* on urban air quality in Paris region.

First, as an alternative PM10 indicator, we employ the number of days with PM10 above 50 $\mu g/\mathrm{m}^3$, which is a warning threshold for urban air quality. (AirParif, 2019)
We always apply a "Difference in Difference" model of estimation, with full set of covariates and entity and time fixed effect.
Table 6 shows that the policy has had a negative and statistically significant impact also on number of days with PM10 above 50 $\mu g/\mathrm{m}^3$, causing a decrease of -50.825 points (last column).
It means that the presence of the electric car-sharing service has caused an annual reduction of the number of days with PM10 above the warning threshold of 50 $\mu g/\mathrm{m}^3$ equal to around 51 days.
This outcome confirms the results obtained using the annual average indicator, bringing further evidence in favour of hypothesis 1.

INSERT TABLE 6 AROUND HERE

Second, as an alternative NO2 indicator, we use the number of days with NO2 above 200 $\mu g/\mathrm{m}^3$, which is a warning threshold for urban air quality. (AirParif, 2019)
We always apply a "Difference in Difference" model of estimation, with full set of covariates and entity and time fixed effect.
Table 7 shows that the policy has had a negative and statistically significant impact also on number of days with NO2 above 200 $\mu g/\mathrm{m}^3$, causing a decrease of -160.21 points (last column).
It means that the presence of the electric car-sharing service has caused an annual reduction of the number of days with NO2 above the warning threshold of 200 $\mu g/\mathrm{m}^3$ equal to around 160 days.
This outcome confirms the results obtained using the annual average indicator, bringing further evidence in favour of hypothesis 3.

INSERT TABLE 7 AROUND HERE

8 Conclusion

In this paper, we investigate the impact of a soft and smart urban mobility policy on the urban air quality.
The hypothesis that our study intends to check is whether the introduction of an electric car-sharing service, namely *Autolib*, in Paris region, has reduced the average levels of three key air pollutants, which are responsible for major health problems in urban area: Particulate Matter (PM10), Nitrogen Oxides (NOx) and Nitrogen Dioxide (NO2) [6].
Our empirical investigation is based on data retrieved from 3 main online open sources (*AirParif* database, *Autolib* website and *Paris Ma Ville* website) and applies a "Difference in Difference" model of estimation, whose employment is partially supported by a preliminary graphical inspections of the data.
The results of the econometric analysis confirm our three hypothesis, showing that Autolib has significantly reduced the average level of PM10, NOx and NO2, determining a decrease of respectively 10%, 12% and 27% with respect to their average level.
Moreover, the robustness checks carried out with the use of some alternative pollutants indicators produce further evidence in support of our results.
As many other empirical investigations, also this one presents some caveats to be mentioned.
First, the data on pollutants fail to pass the graphical test for the parallel trends assumption, which would provide a relevant qualitative support to our estimation model.
However, the results of the inspection on pollutants' absolute trends provides a partial backing to the "Difference in Difference" model.
Second and main issue is represented by endogeneity, due to two possible causes: 1) other factors affecting pollutants levels, which might be overlooked, and 2) the not random assignment of the treatment (electric cars stations could be deployed where the pollutant levels are already lower or show declining trends).
The first cause of endogeneity, which is responsible for a possible omitted variable bias of the estimations, has been tackled by including a list of relevant covariates.
The second cause of endogeneity could be overcome by using the *Propensity Score Matching* (PSM) method, which allows to reduce the possibility of bias due to the difference in the average outcome between treated and untreated

[6] Some investigations have been carried out also on PM2.5 and Tropospheric Ozone (O3), but the paucity of data prevented us from conducting any reliable empirical analysis.

groups, caused by a factor that predicts treatment rather than treatment itself. Unfortunately, the PSM solution cannot be applied because the dataset is composed by too few data.
However, our results are robust to the introduction of both station and department fixed effects, which control for the variables affecting pollution at monitoring station and department level.
Moreover, in spite of the fact that the assignment of the policy (treatment) is not random, but depends on a series of factors which can be correlated with pollution levels (outcome variables), the assignment is at least heterogeneous across departments and *arrondissments*; in fact, the treated areas are both in centre and in peripheral zones, thus covering areas with different traffic and pollution patterns.
Another issue that could arise handling environmental data is represented by the spatial correlation, that is when dependant variables, independent variables and/or errors show spatial correlation patterns.
A way to detect the presence of spatial correlation is the Moran test, which verifies residual correlation with nearby residuals. However, we were not able to perform such test, because of the unavailability of data on the spatial coordinates of the observations (they are necessary to construct a weights matrix). However, we try to prevent our study from suffering from possible spatial correlation issue, by running a spatial autoregressive model for panel data without coordinates, which, unfortunately, did not produce any result because of insufficient observations.
A further space-related issue is represented by the fact that our study relies on the assumption that the *Autolib'* cars available within an arrondissment are expected to be used and impact the traffic (and pollution) only within that arrondissment, while actually they could overcome the neighbourhood's 'frontiers'. This assumption is rather strong, even though it is credible that car-sharing cars are mostly used for short-run trips.

Despite these caveats, the study brings about interesting policy implications, since our empirical results show that the promotion of a "soft and smart" mobility policy, taking the form of the introduction of an electric car-sharing service, is beneficial for the environment, with subsequent positive effects also on the health outcomes in the metropolitan area.
Therefore, this study opens up stimulating avenues of further research in the area of "soft policy" evaluation in the urban context. In fact, it would be of interest to further investigate the environmental and health impact of others soft mobility policies, which encourage the voluntary use of sustainable means of transport, in order to achieve the urban environmental and health quality goals.

Table 1: List of AirParif stations and Autolib localization

AirParif Station	*Département*	*Arrondissment*	*Autolib*
Paris Centre	Paris	I-IV	YES
Tour Eiffel	Paris	VII	YES
Champs Elisées	Paris	VIII	YES
Place Victor Basch	Paris	XIV	YES
Boulevard Peripherique Auteuil	Paris	XVI	YES
Paris 18éme	Paris	XVIII	YES
Gennevilliers	Hauts-de-Seine	Nanterre	YES
La Défense	Hauts-de-Seine	many	YES
Bobigny	Seine-Saint-Denis	Bobigny	YES
Villemomble	Seine-Saint-Denis	Bobigny	YES
Tremblay en France	Seine-Saint-Denis	Le Raincy	YES
Nogent sur Marne	Val-de-Marne	Nogent-sur-Marne	YES
Champigny sur Marne	Val-de-Marne	Nogent-sur-Marne	YES
Cachan	Val-de-Marne	Hay-les-Roses	YES
Vitry sur Seine	Val-de-Marne	Créteil	YES
Lognes	Seine-et-Marne	Torcy	NO
Melun	Seine-et-Marne	Melun	NO
Mantes-la-Jolie	Yvelines	Mantes-la-Jolie	NO
Montgeron	Essonne	Evry	YES
Les Ulis	Essonne	Palaiseau	NO
Cergy-Pontoise	Val-d'Oise	Pontoise	NO
Gonesse	Val-d'Oise	Sarcelles	NO

Table 2: Summary statistics

Variable	**Mean**	**Variance**	**Min**	**Max**	**N. Obs**
Annual average PM10	27.2	62.25	17	50	183
Annual average NOx	80.77	7005.51	19	405	253
Annual average NO2	38.06	449.24	15	114	268
N. days PM10 above 50 mg/m3	27.8	974.7	0	149	182
N. days NO2 above 200 mg/m3	10.6	1601	0	312	258
Autolib	0.39	0.24	0	1	286
Vélib	0.38	0.24	0	1	286
Zone20	0.35	0.23	0	1	169
Zone30	0.44	0.25	0	1	182
ZCR	0.02	0.02	0	1	286

Table 3: Difference in Difference over annual average PM10 levels

	(1) PM10	(2) PM10_1	(3) PM10_1	(4) PM10_1	(5) PM10_1
POST_2011	-6.013***	3.521	0.594	-3.209	-3.209
	(1.066)	(2.157)	(4.430)	(1.693)	(1.693)
Autolib	21.045***	12.797***	14.685***	2.780**	2.780**
	(0.859)	(2.586)	(2.971)	(0.931)	(0.931)
POST_2011_AUTOLIB	-15.766***	-16.655***	-18.953***	-3.367***	-3.367***
	(1.391)	(3.117)	(3.311)	(1.089)	(1.089)
Vélib		10.641***	10.987***	-1.132	-1.132
		(1.805)	(1.595)	(0.667)	(0.667)
zone20		-9.270***	-9.275***	1.228	1.228
		(2.594)	(2.525)	(0.734)	(0.734)
zone30		-1.041	-0.429	-0.168	-0.168
		(2.693)	(2.659)	(0.647)	(0.647)
ZCR		-3.174	-1.034	-0.128	-0.128
		(2.277)	(3.102)	(1.931)	(1.931)
YEAR	NO	NO	YES	YES	YES
STATIONS	NO	NO	NO	YES	YES
DEPARTMENTS	NO	NO	NO	NO	YES
_cons	27.955***	26.602***	27.000***	37.332***	37.332***
	(0.859)	(1.241)	(3.490)	(0.780)	(0.780)
N	183	110	110	110	110
R^2	0.088	0.443	0.475	0.980	0.980

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Difference in Difference over annual average NOx levels

	(1) NOx	(2) NOx	(3) NOx	(4) NOx	(5) NOx
POST_2011	-42.064***	-30.997*	-18.764	-17.725*	-17.725*
	(7.573)	(13.762)	(47.118)	(8.041)	(8.041)
Autolib	278.211***	206.979***	231.337***	7.320	7.320
	(7.498)	(32.354)	(35.871)	(5.281)	(5.281)
POST_2011_AUTOLIB	-226.776***	-171.807***	-207.539***	-12.092**	-12.092**
	(11.730)	(33.011)	(34.463)	(5.657)	(5.657)
Vélib		80.198***	103.975***	-9.728*	-9.728*
		(18.353)	(15.816)	(4.585)	(4.585)
zone20		-31.983	-32.770	6.107	6.107
		(34.544)	(37.732)	(4.433)	(4.433)
zone30		-2.868	-9.503	-0.194	-0.194
		(33.693)	(34.641)	(3.154)	(3.154)
ZCR		-40.780	-96.194	-6.661	-6.661
		(39.543)	(49.306)	(11.153)	(11.153)
YEAR	NO	NO	YES	YES	YES
STATIONS	NO	NO	NO	YES	YES
DEPARTMENTS	NO	NO	NO	NO	YES
_cons	80.789***	74.691***	111.250**	173.768***	173.768***
	(7.498)	(12.818)	(36.197)	(6.214)	(6.214)
N	253	142	142	142	142
R^2	0.078	0.212	0.255	0.994	0.994

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Difference in Difference over annual average NO2 levels

	(1) NO2	(2) NO2	(3) NO2	(4) NO2	(5) NO2
POST_2011	-16.654***	-11.330**	-15.273	-6.387**	-6.387**
	(2.007)	(3.588)	(10.727)	(1.906)	(1.906)
Autolib	74.317***	57.601***	62.272***	8.714***	8.714***
	(1.920)	(8.406)	(9.815)	(1.941)	(1.941)
POST_2011_AUTOLIB	-57.137***	-47.167***	-54.792***	-11.005***	-11.005***
	(2.873)	(8.491)	(9.582)	(2.084)	(2.084)
Vélib		22.216***	27.728***	-0.905	-0.905
		(4.347)	(3.747)	(1.084)	(1.084)
zone20		-6.378	-5.189	0.939	0.939
		(8.601)	(9.524)	(1.421)	(1.421)
zone30		-3.388	-4.925	1.193	1.193
		(8.642)	(8.896)	(1.216)	(1.216)
ZCR		-8.754	-15.948	-2.136	-2.136
		(10.486)	(12.686)	(2.547)	(2.547)
YEAR	NO	NO	YES	YES	YES
STATIONS	NO	NO	NO	YES	YES
DEPARTMENTS	NO	NO	NO	NO	YES
_cons	39.683***	37.571***	46.667***	67.433***	67.433***
	(1.920)	(3.081)	(7.884)	(1.083)	(1.083)
N	268	152	152	152	152
R^2	0.119	0.267	0.302	0.990	0.990

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Difference in Difference over the n. of days with PM10 > 50 μg/m3

	(1) PM10	(2) PM10_2	(3) PM10_2	(4) PM10_2	(5) PM10_2
POST_2011	-13.711**	18.642*	7.050	-11.093	-11.093
	(4.114)	(8.733)	(17.200)	(13.295)	(13.295)
Autolib	119.466***	85.818***	97.972***	41.090***	41.090***
	(3.574)	(12.231)	(12.745)	(8.185)	(8.185)
POST_2011_AUTOLIB	-105.987***	-107.854***	-118.603***	-50.825***	-50.825***
	(5.268)	(13.997)	(14.850)	(10.441)	(10.441)
Vélib		39.488***	38.418***	5.236	5.236
		(8.409)	(7.634)	(4.478)	(4.478)
zone20		-32.747**	-30.529**	19.271**	19.271**
		(11.942)	(11.055)	(6.711)	(6.711)
zone30		-1.127	1.860	-10.435	-10.435
		(13.120)	(12.327)	(5.953)	(5.953)
ZCR		-19.759*	-12.586	-5.263	-5.263
		(7.661)	(11.246)	(13.127)	(13.127)
YEAR	NO	NO	YES	YES	YES
STATIONS	NO	NO	NO	YES	YES
DEPARTMENTS	NO	NO	NO	NO	YES
_cons	28.534***	23.821***	24.000	49.457***	49.457***
	(3.574)	(4.469)	(12.336)	(4.562)	(4.562)
N	182	110	110	110	110
R^2	0.098	0.387	0.444	0.916	0.916

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Difference in Difference over the n. of days with NO2 > 200 μg/m3

	(1) NO2_D	(2) NO2_D	(3) NO2_D	(4) NO2_D	(5) NO2_D
POST_2011	-11.780**	-7.774	-7.557	-21.447	-21.447
	(3.785)	(5.153)	(14.855)	(23.037)	(23.037)
Autolib	285.120***	250.175***	264.014***	151.504***	151.504***
	(3.783)	(13.921)	(14.298)	(23.130)	(23.130)
POST_2011_AUTOLIB	-276.093***	-252.299***	-268.250***	-160.209***	-160.209***
	(4.962)	(13.848)	(14.845)	(22.846)	(22.846)
Vélib		21.218	23.967*	0.942	0.942
		(10.742)	(9.214)	(8.674)	(8.674)
zone20		-24.085	-24.396*	22.313	22.313
		(14.162)	(12.140)	(14.742)	(14.742)
zone30		12.832	16.603	-11.929	-11.929
		(15.863)	(15.375)	(12.699)	(12.699)
ZCR		-17.909*	-24.485*	13.612	13.612
		(7.940)	(10.023)	(22.013)	(22.013)
YEAR	NO	NO	YES	YES	YES
STATIONS	NO	NO	NO	YES	YES
DEPARTMENTS	NO	NO	NO	NO	YES
_cons	11.880**	12.776**	15.667	6.511	6.511
	(3.783)	(4.872)	(11.093)	(7.705)	(7.705)
N	258	146	146	146	146
R^2	0.208	0.283	0.303	0.799	0.799

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3: Île de France and its departments

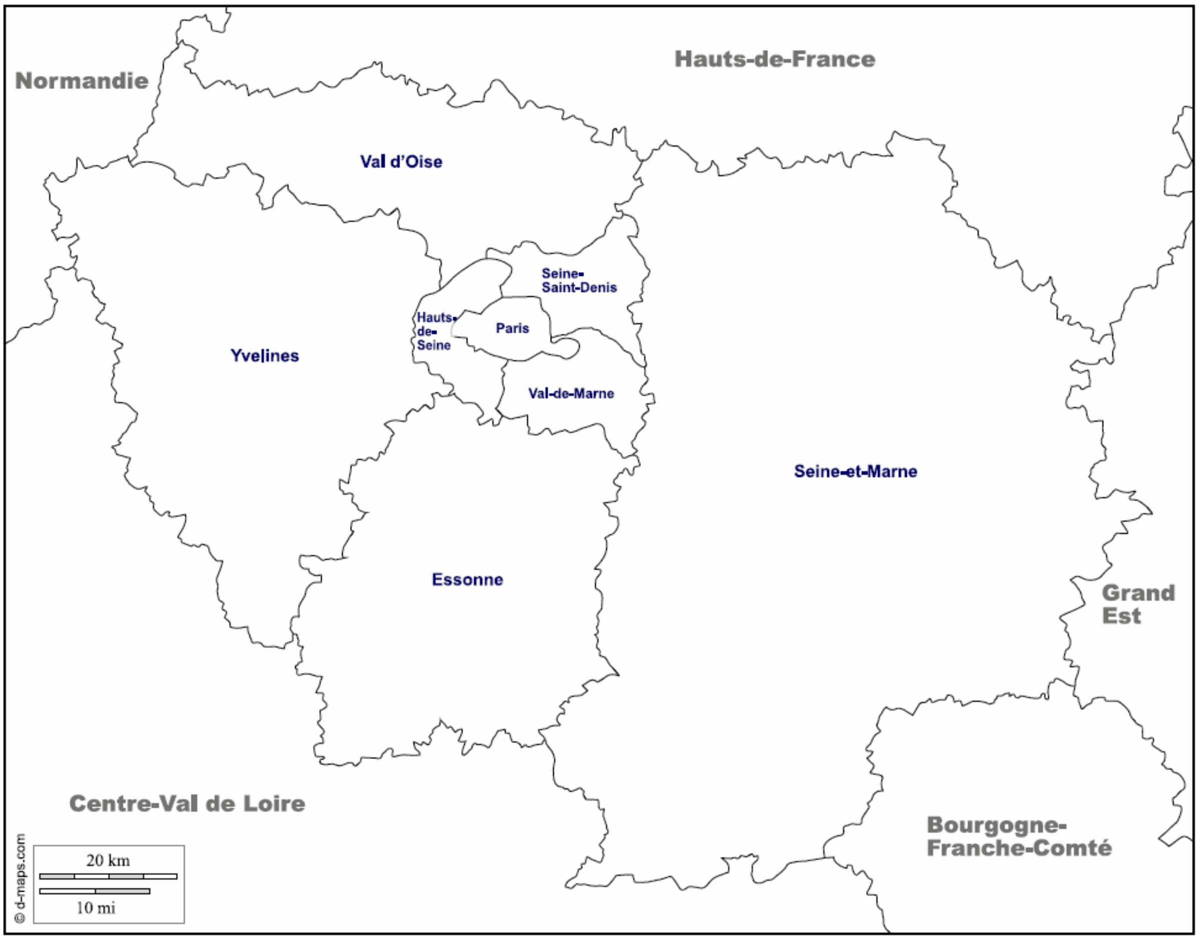

Figure 4: Île de France and its arrondissments

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