SEEDS
Sustainability Environmental Economics and Dynamics Studies

Working Paper Series

Environmental policy and invention crowding out. Unlocking the automotive industry from fossil fuel path dependence

by

Nicolò Barbieri

6/2015

SEEDS Working Paper 6/2015
March 2015
by Nicolò Barbieri

Environmental policy and invention crowding out. Unlocking the automotive industry from fossil fuel path dependence

Nicolò Barbieri*

Abstract

This paper aims to shed light on the drivers that encourage a shift from incumbent internal combustion engine technologies towards low-emission vehicle technologies. We emphasise the role of fuel prices, one of the main drivers of environmental innovation, and other features of the technology space (such as technological proximity), in impacting technological dynamics and fossil fuel technological lock-ins. Specifically, we investigate whether green technological efforts come at the expense of other environmental or non-environmental inventive activities.

In doing so, we employ Self-Organised Maps (SOMs) to detect the main technological domains exploited by the automotive industry during the period 1982-2008, using triadic patent families as a proxy for technological efforts pursued in each technological field.

On the one hand, we test whether these drivers foster the substitution of non-green patents with green ones. On the other, we analyse if they favour substitution between technological efforts related to alternative vehicles, de facto influencing low-emitting vehicle competition.

Our findings suggest that higher tax-inclusive fuel prices (used as a proxy for carbon tax) are effective in redirecting patenting activities from non-green to green technological fields. In addition, we observe a similar impact when we focus on green technological fields. Although this result may involve the risk of potential lock-in into sub-optimal substituting technologies, there are insights that the competition within the environmental technological domain mainly regards technological efforts spent on greening conventional cars and developing low-emission vehicles.

Keywords: Environmental technologies; Self-Organising Maps; Crowding out; Fuel prices; Patent data.

J.E.L.: O32, Q55, L62

* Corresponding author: Department of Economics - University of Bologna, Strada Maggiore, 45 - 40125 Bologna, Italy. E-mail: n.barbieri@unibo.it

1 Introduction

'La Jamais Contente', invented by Camille Jenatzy in 1899, was the first electric vehicle that went over 100 km/h (Armand and Tarascon, 2008). It provides an insight into how the car market was structured at the end of the 19th century when different technologies (i.e. steam, electric and gasoline cars) competed for a market in which no technology dominated (Basalla, 1988). However, at the turn of the century, gasoline cars reached an advantage mainly driven by economic and technical factors such as mass production and rapid solution to technical problems (i.e. engine start, water consumption, low maximum speed, etc.), consolidating the dominant position of internal combustion engine vehicles (ICEVs) within the automotive industry (Cowan and Hultén, 1996). Although in the 1970s, fundamental changes affected the car market; growing concern over traffic congestion and air pollution, as well as oil crises, contributed to modifying the economic and social factors that governed technological developments in that industry. Since then, different technological trajectories have taken place, increasing the variety of low-emission vehicles (LEVs) that compete with ICEVs, i.e. electric (EV), hybrid (HV) and fuel cell (FCV) vehicles.

The economic metaphor that can be drawn from this story is that, even if these alternative technological trajectories provide improved environmental performance that is able to meet current needs, evolutionary economists emphasise that the process of technology selection is path dependent, not predictable ex ante and irreversible, and thus, the market may select sub-optimal technologies due to increasing returns to adoption (Arthur, 1989; Bruckner et al., 1996; Frenken et al., 2004). This conservatism in market selection, on the one hand, negatively affects the probability that alternative technologies will be adopted ('self-reinforcement') and, on the other, allows producers to take advantage of economies of scale and R&D investments (David, 1985)[1]. In addition to path dependence in technology adoption, Acemoglu et al. (2012) states that a path-dependent process characterises the type of innovation that is produced, providing incentives for firms that spent innovative efforts in dirty technology in the past to innovate in dirty technologies in the future.

Moreover, it should be noted that the evolutionary process at the basis of technological change emphasises that the success of technological advances cannot be determined ex ante (Nelson and Winter, 1982). This is mainly due to the uncertainty that surrounds design and planning processes. Indeed, successful technological advances are the result of a process in which, at any time, a range of technological opportunities is undertaken and proposed to the selection environment (Gelijns et al., 2001). Therefore, there is competition between innovations and what determines a prevailing technology is the result of ex post selection (Gelijns et al., 2001).

In this regard, it is pointed out that technological uncertainty also affects the development of low-emission vehicles. Indeed, a first source of uncertainty is linked to the capability of alternative cars to substitute conventional vehicle designs, whereas the second is mainly related to competition *between* alternative vehicles due to the fact that, in the current state, it is unclear which alternative option should be preferred from both an economic and environmental perspective (Frenken et al., 2004).

In this complex framework where uncertainty, path-dependence and competition (ICEVs vs. LEVs and between LEVs) stand out, several authors highlight that policy intervention may represent one of the main factors that will allow socio-technical lock-ins to be overcome (Faber and Frenken, 2009; Rennings et al., 2013), and specifically, ICEV lock-in to be avoided (Cowan and Hultén, 1996)[2]. During recent decades, many authors have highlighted the role of environmental policies in

[1]In David (1985), the author ascribed QWERTY lock-in to technical interrelatedness, economies of scale and quasi-irreversibility of investment.

[2]The authors identified, in addition to regulations, other factors such as crisis in the existing technology, technological breakthrough, changes in taste, niche markets and scientific results (Cowan and Hultén, 1996).

inducing the development of environmentally-sound technologies (Popp et al. 2010; Bergek et al., 2014). However, when technologies compete, even if it has been emphasised that environmental policies lead to increasing innovative performances and market competitiveness (Porter and van der Linde, 1995), the production of eco-innovation sometimes causes secondary effects; these include environmental rebound, green paradox and crowding-out (van den Bergh, 2013).

In this regard, environmental policies lead to higher opportunity costs that derive from real resource requirements (financial and human resources) to develop and adopt alternative technologies needed to comply with policy requirements (Jaffe et al., 2002). Therefore, they may trigger innovation in green technological domains that drive away inventive activities from non-environmental and/or environmental ones, thus becoming a potential source of innovation crowding out.

This paper delves into the broad range of factors that influence innovation dynamics in a sample of automotive firms, focusing on the effectiveness of environmental policy in unlocking innovation from ICEV technologies. In this regard, the presence of a crowding out effect may favour achieving this objective because, even if crowding out of every type of innovation reduces social benefits[3] and eventually decreases competitiveness, it may contribute to unlocking the automotive industry from fossil fuel path dependence, i.e. decreasing ICEV innovation efforts in favour of those related to LEVs.

Apart from a few exceptions which are discussed in the next section, this topic remains almost unchartered and only a very small portion of the debate is focused on the policy-driven crowding out effect. In addition, the main lack in this literature is the study of “what” is being crowded out. Therefore, if improvements in technologies with negative environmental effects are crowded out to favour green technological advances, the costs of crowding out for the society will be hampered (Popp, 2005), or otherwise increased if crowding out affects other environmental technological efforts. Thus, we test whether innovative efforts on environmental technologies come at the expense of other eco-innovations.

The paper is structured as follows: Section 2 introduces the related literature and Section 3 explores the main features that characterise the automotive technological system presenting the data and identifying the main technological trajectories through Self-Organising Maps (SOMs). Section 4 describes how we build our main variables and the empirical model whereas Section 5 discusses the results. Finally, Section 6 concludes.

2 Literature review

In a recent overview of the studies that investigate eco-innovation from an evolutionary perspective, Cecere et al. (2014) emphasises that technological, social, organisational and institutional lock-ins affect environmental innovation development and adoption.

In this framework, firm-level strategies, technological niches and regulations are keys to overcoming path dependence on dominant technological designs. In particular, an outstanding branch of literature provides evidence of the effectiveness of environmental policy in boosting eco-innovation (surveyed in Popp et al., 2010), shedding light on its potential to unlock the technological system. Indeed, studies on environmental regulations have been finalised to assess whether environmental policy fosters technological change towards a more sustainable path. However, the literature does not provide insights into the potential shift from non-green inventions to green ones.

In order to understand the overall effect of green regulation on the economic system, we study its potential, secondary consequences, i.e., the potential crowding out effect, that eco-innovation may

[3]The social returns to research are greater than private returns for firms (Mansfield et al., 1977; Pakes, 1985; Jaffe, 1986)

have on other innovation, should be investigated to appreciate the overall impact beyond the development of new green technological efforts.

Environmental innovation may come at the expense of non-green ones or be complementary to them in firms' innovation portfolios. In both cases, it is important to investigate the role of environmental policies to assess how technological systems can escape fossil fuel lock-in. However, the literature on the crowding out effect has been limited by the difficulty in addressing the issue empirically. In addition, it is arduous to distinguish, even ex post, whether a change in innovation activities has been caused by policy intervention or by research opportunities and firm strategies.

Whereas conventional wisdom predicts that environmental policy interventions decrease the productivity of optimising firms, evolutionary economists maintain that regulated firms improve their innovative efforts which, in turn, cause an upsurge in their economic performance (Porter and van der Linde, 1995).

In this regard, when addressing the issue of the effects that the development of innovation may cause, a new stream of literature has analysed the opportunity cost of environmental innovation. This opportunity cost, caused by a "crowding out effect" and indirectly connected to the policy framework (i.e. technical and economic resources that compliance behaviours may require), impacts on the effectiveness and efficiency of environmental policies in unlocking the industry. If improvements in technologies with negative environmental effects are crowded out to favour green technological advances, the costs of crowding out for the society will be lower (Popp, 2005) than if it impacted other environmental technological efforts.

One of the seminal works that discuss the presence of a crowding out effect is Gray and Shadbegian (1998). The authors examine the impact of environmental regulation stringency in the pulp and paper industry. In their study, crowding out affects investment decisions on pollution abatement and productive (non-environmental) capital investments. The results seem to provide evidence that pollution abatement investments crowd out other productive investments in high polluting plants.

Marin (2014), using a dataset of Italian manufacturing firms, provides insights (at least in the short run) that environmental innovation comes at the expense of non-environmental innovation. This possible evidence of crowding out is mainly driven by the lower return that distinguishes eco-innovation from other investments coupled with the constrained financial resources devoted to R&D activities.

When firms are not financially constrained, a decrease in non-environmental innovations, caused by an increase in eco-innovation, does not always imply that the crowding out effect reduces social and private benefits. Popp and Newell (2012) investigates whether the increase in climate R&D spending induces a lower level of R&D investments in other fields. First, the authors find no evidence of crowding out across sectors 'mitigating the concern that new energy R&D programs will draw resources away from other innovative sectors of the economy' (Popp and Newell, 2012; pp. 990). Second, using patent data as a proxy for R&D expenditure, they examine whether this hypothesis holds within sectors, finding that an increase in alternative energy patents leads to a decrease in other patents. However, the absence of financial constraints for those firms may prove that the crowding out effect has been driven by changes in market opportunities. This result underlines the positive environmental effect of crowding out that seems to induce the development of greener technologies at the expense of dirty ones, facilitating the achievement of environmental policy objectives.

More evidence of an R&D offset comes from Kneller and Manderson (2012). Their results highlight that an increase in environmental compliance costs boosts environmental innovation. Although, the effect of environmental expenditures does not positively impact the total amount of R&D investments, suggesting that environmental R&D crowds out non-environmental R&D[4].

Mainly due to the research questions they answer, these studies focus on the environmental innovation effect without directly examining the role of environmental policies. An exception is

[4] The authors highlighted that there is no evidence that environmental capital crowds out non-environmental capital.

Hottenrott and Rexhäuser (2013) that employs survey-based data in order to detect which firms introduce environmental technologies as a consequence of policy compliance behaviour. The study suggests that while there is evidence that environmental innovation crowds out firms' in-house R&D expenditure, this does not seem to influence the number of existing R&D projects, their outcome or the amount of investments in fixed assets (both innovation-related and others). In addition, the authors advocate that firms prefer scaling down long-term oriented R&D activities that are not directly connected to production and that provide relatively uncertain returns.
Our paper takes advantage of the findings of these studies to analyse whether environmental policy stringency encourages a shift from non-environmental inventions to environmental ones. In doing so, we fill the gap in the literature that assesses the effectiveness of environmental policy in unlocking the technological system from path dependence on non-environmental inventive efforts. Therefore, the first research question is the following:

- Does environmental policy induce a shift from non-environmental invention to environmentally friendly inventive activities?

Finally, two main propositions are put forward from the literature on technological substitution (David, 1985; Arthur, 1989). First, even if substituting technologies are available and superior to the dominant one, technological substitution is not assured due to the presence of increasing returns to adoption. Second, in a technological substitution process, a pool of new technologies compete for dominance although lock-ins into sub-optimal substituting technologies are still possible due to path dependence of sequential adoption decision. With regard to these points, in the automotive industry both propositions apply, at least in part, due to the presence of competition between conventional and low-emitting vehicles and between alternative vehicles designs that may substitute conventional cars (Frenken et al., 2004).
Due to the fact that the potential shift from non-green to green inventions may also affect the environmental domain because of competition between low-emitting vehicle technologies, i.e. green inventions come at the expense of other green inventions, we investigate 'what' has been crowded out. In this case, if environmental policies drag away resources from environmental technological domains to develop other green inventions, the risk of technological change lock-ins into a sub-optimal substituting technology will be higher because of the absence of a superior alternative technology, from both an economic and environmental perspective, at the current stage. This leads to the second research question:

- Does environmental policy alter competition between alternative low-emissions vehicles? Does it cause a shift among environmental inventive activities?

3 The automotive technological system

3.1 Patent data in the automotive sector

In order to answer the abovementioned research questions, our study focuses on large-size incumbent automotive firms. The motivations that support this choice are manifold. First, due to its high impact on local and global air pollution, policy makers all over the world have advocated the need to decrease the emission of pollutants released by vehicles. To do so, many efforts have been made, especially over the last decades, regarding the environmental regulatory system to hamper transport sector environmental impacts. Second, many scholars have highlighted the presence of carbon lock-ins in the automotive industry (Cowan and Hultén, 1996; Frenken et al., 2004; Aghion et al., 2012). Third, the industry had been challenged by deep structural changes, especially over the last few years. The industry has been hit hard by recent financial uncertainty, imposing a reconsideration of knowledge capital management (Laperche et al., 2011). In addition to the dynamics that have characterised the industry from this perspective (R&D rationalisation; R&D collaboration; etc.), the increasing demand for low-emitting vehicles, together with environmental regulations, has provided the incentives to develop new environmentally-sound technologies and reduce vehicle emission levels. Finally, intellectual property (in particular patent protection) assumes, especially in the automotive industry, a pivotal role for triggering profits and competitive advantage (Laperche et al., 2011).

Since our paper aims to explore the dynamics of inventive efforts made in different technological fields, we employ patents as a proxy for invention. Griliches (1990) points out that patents sorted by their priority year have a strong correlation with R&D expenditures. In addition, patents are the only kind of data that provide information on the technical features of inventive activities, essential information to test our hypotheses. However, we must be aware of patent data limitations (see, for example, Griliches, 1990). The main problems arise from variability in their quality (Lanjouw et al., 1998) and from their selection process (keyword search; patent classification search; etc).

In this paper, we employ a methodology based on triadic patent families defined by the OECD as a "set of patents taken at the EPO, USTPO and JPO that share one or more properties" (Dernis and Khan, 2004; pp.17). One of those properties is that patents must pertain to the same patent family[5]. In doing this, we focus on high quality patent data since most important inventions are protected in these three patent offices. Moreover, we reduce the influence of the heterogeneity of patent offices' regulation systems (Dernis and Khan, 2004). In addition, to deal with patent sample selection problems that come from the type of search that is carried out[6], we collected the automotive firms included in the R&D scoreboards (IRI) from the 2006-2011 editions[7]. In doing so, we focus on firms that perform constant and considerable amounts of R&D investment. Indeed, incumbent firms are expected to carry out large R&D programmes thanks to consolidated financial and R&D capabilities (Cohen and Klepper, 1996). Subsequently, we gathered the patents filed by those 71 firms, retrieving their name from the Derwent Corporate Tree[8] in order to obtain the whole corporate structure and their standardised applicant names. This process allows us to account for the complex globalised structure of the automotive industry and reduce noise caused mainly by spelling variations in assignees' names.

3.2 Self-Organising Maps

We collected all the patent family applications filed by the former sample of firms from the Thomson Innovation database obtaining a total of 247,510 patent families, of which 54,371 are triadic patent families (TPFs). In addition, we discerned between green and non-green TPFs by exploring their technological classification codes. Different technological classification have been proposed to analyse the technological content of patent data. In this paper we use Cooperative Patent Classifications (CPC) codes[9], which provide a hierarchical and language independent

[5] Patent families are defined by the OECD as "the set of patents (or applications) filed in several countries which are related to each other by one or several common priority filings" (OECD, 2009; pp.71).

[6] Many ways to collect patents are adopted in the literature. However, relevant drawbacks are associated with patent classification searches (Costantini et al., 2013) and applicant name searches (Thoma et al., 2010).

[7] Before 2006 and after 2011, R&D Scoreboard editions the number of firms ranked was different from that of 2006-2011 (500 and 2000 instead of 1000 firms). The 2006-2011 editions are therefore homogeneous and comparable.

[8] The Corporate Tree tool covers the top 2,500 patenting companies for those authorities and takes into account mergers, acquisitions, divestitures, spelling differences (but not reassignments). Six firms were not included in the Corporate Tree tool. For these we found the patent in the OECD "Harmonised Applicants' Names" database by searching the applicant name field.

[9] CPC is a new classification introduced in the USPTO and EPO that includes a section for emerging technologies (http://www.cooperativepatentclassification.org). For an application of CPC patent maps, see (Leydesdorff et al., 2013)

classification of patent technical domains. In particular, what makes this classification appealing for our study is the possibility of detecting green patents through the Y02 class "Technologies or applications for mitigation or adaptation against climate change" that we use to identify the environmental inventions in our dataset.

Figure 1 illustrates the trends in green and non-green TPF applications sorted by their earliest priority year. We can appreciate from the histograms that the percentage of green TPF per year steadily rose from 1980 to 2006 (when it reached its maximum) and then gradually fell until 2009, whereas the percentage of non-green patents followed the opposite trend. Moreover, we can appreciate that the percentage of green and non-green TPFs over the total (respectively, green and non-green) TPF applications in the whole period, sharply increased from 1990 onwards. However, while the percentage of non-green patents has fluctuated since 2000, the one related to green patents continued to grow until 2006. These issues highlight that the distribution of green patents grew in recent years probably due to environmental policy efforts made in both greening ICEV technologies and developing new alternative vehicle propulsion systems.

However, in order to investigate which inventive activities may impact technological advance dynamics, we further discerned between the type of technologies that are included in the green and non-green technological fields. In doing so, we assume that the share of CPC classes between inventions represents a proxy for their technological similarity, i.e. the higher the number of CPC classes that occur among the patents, the greater their technological relatedness. Unlike other approaches that use patents to measure the relatedness between technological fields (Jaffe, 1986; Nesta and Saviotti, 2005; Breschi et al., 2003; to cite a few), we employ technological fields to map inventions based on their technological similarity[10].

Thus, we created a distance-based patent map using a Self-Organising Map (SOM) mapping technique (Kohonen, 1990; 2001). The SOM is a unsupervised neural network that represents multidimensional data in a two-dimensional space which returns the similarity between input data. The process is based on a map of interconnected nodes to which the input items are assigned according to the Euclidean distance (ED) between nodes' weight vectors and input vectors. Figure 2 (a) shows how input data have been introduced in the present exercise, i.e. each row represents a patent, the columns denote CPC codes and matrix values indicate whether a CPC is assigned to the patent (1) or not (0).

Since the technicalities of this methodology are described in detail elsewhere (Kohonen, 1990; 2001; 2012; Vesanto, 1999), we will briefly describe the output of this process.

After the initialisation step, where the weights are assigned to the empty map (Figure 2b), a batch algorithm (Kohonen, 2013) is implemented. In each step, the SOM randomly selects an input (in our case a patent) and detects the map node with the lowest ED (Best Matching Unit - BMU) between it and the initialised nodes of the maps (Figure 2c). This step is iterated until each input is assigned to a map node. Subsequently, a radius defines the neighbours for each BMU, i.e. a set of nodes close to the BMU (Figure 2d). Finally, the neighbour node weights are modified to become more similar to the BMU, and pushed closer to the BMU. This feature allows the map to represent the similarity between the input data, decreasing the distance between similar map units and, therefore, increasing the one between different units.

The advantages of using the SOM are manifold. We are able to i) locate patents in a technology space that returns the similarity between them (the more their technological contents are similar, the more they are closely mapped); ii) define patent clusters that refer to the same vehicle component (e.g. hybrid engine; catalytic converts; batteries; brakes; etc.) and iii) measure the relatedness between these clusters. In comparison to other techniques and methodologies to retrieve the

[10] Other works have focused on patents to "link" technological fields, i.e., the presence of technological fields between two patents represents proof of the relatedness between the fields. In our exercise, we look at the presence of technological fields to relate patents, i.e. the greater the number of classification codes shared, the higher the similarity in the patents' technological contents.

cognitive distance between technological fields, the SOM provides a distance-based output where the patents are located according to their global and local similarity.

3.3 Exploring the technological space

In order to define the technological clusters, we applied the non-hierarchical k-means clustering technique (MacQueen, 1967) on the SOM output, obtaining 31 clusters[11]. The SOM and k-means algorithm outputs are illustrated in Figure 3. Figure 3a shows the distance between nodes and their closest neighbours, i.e. the Unified-distance Matrix (UMAT), whereas Figure 3b reports results of the k-means clustering process applied to the SOM.

Table 1 lists the main keywords[12] associated with the 31 invention clusters that the combined procedure has detected. In addition, the right columns of the table provide the number of patents in each cluster and the percentage of green patents. It is noteworthy that the clustering exercise has correctly identified and placed green inventions creating clusters consisting almost entirely of environmental patents.

As far as the location in the map is concerned, Figure 3 clearly illustrates that green inventions are located at the bottom of the technology space. Looking at this portion of the figure from left to right, we can observe the variety of LEV technologies that have influenced the main technological trajectories in alternative vehicles. On the left, Cluster 6 and 12 comprise hybrid vehicle (HV) technologies that integrate the ICE and the electric motor (Dijk and Yarime, 2010). This technology is considered promising, at least in the short run, for the transition from ICEVS to FCVs (Oltra and Saint Jean, 2009). Indeed, moving to the right of these two clusters, the technological space focuses on batteries implemented in HVs and EVs. Specifically, inventions in Cluster 9, 10 and 22 exploit alternative system of batteries that represent the main barrier to a sizeable electric car market. The technological variety in LEVs is completed by Cluster 20 that embraces fuel cell vehicles. Finally, in Cluster 2, 8, 27 and 31, we can retrieve technologies that reduce the impact of ICEVs such as catalytic converters, turbochargers, direct injection, etc. These technological improvements regard what we have referred to previously as the greening of persistent dominant design in the automotive industry.

What is more, the rest and the majority of the technological space is characterised by non-green inventions. In the centre of the map, Cluster 11 appears to have the highest share of nodes compared with other clusters. This is confirmed by the fact that almost one third of the patents are included in it. This cluster contains heterogeneous components such as mechanical and electronic apparatus (e.g. air conditioning systems, automatic door opener, etc.) and car designs that are not directly related to the powertrain system. In addition, we can observe two main directions of technological advances that begin from the area closer to green technologies towards the upper side of the map. On the one hand, Cluster 4, 5, 25, 19, 17 and 1 contain patents related to engine mechanical components and catalytic converters. The former refers to technologies linked to the powertrain system, while the latter to systems that regard end-of-pipe technologies outside the realm of green technologies (e.g. silencers). On the other hand, the left part of the map is characterised first by inventions related to the battery system (Cluster 30 and 7) and other elements such as cruise assistance (Cluster 26) and control systems (Cluster 16). A separate discussion is necessary for

[11]The k-means is run multiple times for each k. The process selects the best alternative with regard to the sum of squared errors. Finally, the Davies-Bouldin index is calculated for each alternative (Davies and Bouldin, 1979).

[12] We collected the title and abstract of each patent per cluster and subsequently examined the text in these groups of word through text mining techniques. After a cleaning process in which we deleted the stopwords (a, the, then, if, etc.) and reduced the words to their stem (stemming becomes stem, automobile becomes automobil, and so on), we weighted each word using the term frequency/inverse document frequency (TF/IDF). Finally, we ranked the weighted words in each cluster and chose the most representative of the first 20 words.

Cluster 13, 14, 15, 21 and 24. Those clusters include mechanical developments in transmission (13-15), suspension (24) and brake systems (21).
Concluding our description of the technological space, we find safety technologies in Cluster (23) and tyres and pneumatics patents in Cluster (3).

4 Testing the crowding out hypotheses

4.1 Dependent variable

In this section we describe the variables used to analyse what influences automotive technological system dynamics. First we describe the dependent variable that allows us to measure the shift in innovative efforts made in each technological field. We calculated the CO variable as follows:

$$\Delta PAT_{z,t} = ma_{z,t} - ma_{z,t-1}$$

where ma is the patent count moving average, z refers to specific clusters defined before and PAT the growth rate in the ma for each cluster. Finally, in order to account for the shift from one technological cluster to the other, we calculate the dependent variable through the following formula:

$$CO_{i,t} = \Delta PAT_{g,t} - \Delta PAT_{ng,t}$$

this is the difference between the growth rate in the patent count moving average in a green cluster (g) and the one related to a non-green cluster (ng). i represents each couple of green and non-green clusters. Therefore, when the CO variable is positive, the growth rate related to green clusters is higher than the one in a non-green cluster. We assume that positive values of this variable imply a shift in the technological advances toward more sustainable technologies.
Similarly, the CO variable can be used to test the potential crowding out effect among green clusters as follows:

$$CO_{s,t} = \left|\Delta PAT_{g1,t} - \Delta PAT_{g2,t}\right|$$

where CO is equal to the difference between two patent count moving averages related to $g1$ and $g2$ (with $g1 \neq g2$) with s representing each couple of green clusters. The absolute value helps us to interpret the results since the output in this case is bidirectional.
Therefore, we test the first and second research questions on a total of $g\ x\ ng\ x\ t$ and $g(g-1)x\ t$ observations respectively[13].
The strength of this approach resides in the capability to account for relative increase (decrease) in patent counts related to both technological clusters (g vs. ng and $g1$ vs. $g2$), i.e. a technological field increases more than in proportion to another.

A possible model for analysing what affects competition between inventive efforts in different technological fields can be written as follows:

[13]The patent count in each green technological fields is compared with every other green field except itself. In addition, due to the fact that the outcome is symmetric (e.g. if the outcome of the comparison between cl2 and cl6 is equal to 1, its opposite, cl6 vs. cl2, is equal to 0), the number of observations has been reduced to avoid double counting.

$$CO_{i,t} = f(\alpha_i, \gamma_{i,t}, EP_{i,t}, PROX_{i,t}, C_{z,t})$$

where the dependent variable, CO, is a function of environmental policy stringency (EP). In addition, we check if technological relatedness provides incentives to shift from ng to g technological efforts by including the $PROX$ variable that captures cognitive proximity between the technological clusters to the model. Moreover, we control for those factors that may influence the propensity to decrease inventive efforts in one technological field in favour of another ($C_{z,t}$). Finally, fixed effects α_i capture the unobservable cluster-pairwise-specific time invariant heterogeneity, whereas $\gamma_{i,t}$ is the cluster-pairwise-specific time trend that accounts for unobservable factors associated with each couple of clusters and varies over time.

4.2 Independent variables

The EP variable is designed to include the main driver of environmental innovative activities in the automotive sector, i.e. post-tax fuel prices.

Over the last decades, a widespread literature has analysed the effect of fuel prices on innovation (see Crabb and Johnson, 2007; Hascic et al., 2009; Aghion et al., 2012; among others). These studies shape a consolidated framework that provides evidence of the positive impact of environmental policy on environmental innovation. What is more, if this variable positively impacts our dependent variable it provides an insight that higher stringency increases the probability that green inventions come at the expense of non-green inventive activities, highlighting that instead of being *additional*, green technological efforts crowd out non-green ones. In this case, we advocate that environmental policies may be effective in reducing path dependence on conventional non-environmental technologies. On the other hand, a negative effect may represent an insight that even if environmental regulation induces firms to enhance their inventive activities in the green field, they do not affect non-green technological improvements, showing their ineffectiveness in redirecting technological advances away from ICEV technologies.

Following Aghion et al. (2012), post-tax fuel prices are here used as a proxy for carbon tax. Due to the fact that fuel prices are available only at the country level, the idea is to apply the following formula to exploit the yearly cluster-level variation of the dependent variable[14]:

$$EP_{i,t} = \sum w_{i,c} EP_{t,c}$$

where EP_t is the tax-inclusive fuel price defined as the average between diesel and gasoline price (Figure 4). $w_{i,c}$ is a cluster-specific weight that captures the importance of country c in both green and non-green clusters. We therefore define for each cluster the weight of country c according to the origin of the assignees and to the number of their patents in the cluster. Therefore, the higher the percentage of patents filed by country c, the greater w_c. In order to avoid potential sources of endogeneity deriving from the correlation between patents and fuel prices (Popp, 2002), we calculate w as a time-invariant weight using data over the whole period 1986-2009. Moreover, due to the fact that the production of inventions in the automotive industry is mainly concentrated in three geographical areas, c corresponds to EU, JP and US[15]. Therefore, EP_c includes the Japanese and American fuel price and the average fuel price between European countries.

Moreover, substitution between the two fields may be driven by the characteristics of the technological space. The $PROX$ variable is included to test the effect of relatedness between the technological fields. Indeed, in the new knowledge search process, firms (through routinised

[14]Aghion et al. (2012) exploited the firm-level variation using the firm share of patents filed at country c.

[15] Different country level fuel prices are tested to build robustness in our results.

behaviour) search in the closest knowledge fields to reduce the uncertainty of the process (Boschma, 2005).
Nelson and Winter (1982) emphasises that what emerges when firms search for new knowledge is often uncertain and unexpected. Therefore, the research opportunities found within clusters at a lower cognitive distance may induce firms to consider those technological fields as potential sources of knowledge to lower uncertainty.
Hence, competition between two clusters may be explained by their cognitive proximity in the sense that closer knowledge base may provide opportunities for further improvements in the technological field under investigation.
The literature provides different ways of measuring cognitive distance. Using a matrix and tracing R&D expenditure from the industry of origin to the industry of use of the resulting products and services, Scherer (1982) assumes that two industries can be considered close if there is a high share of R&D performed in one industry and used in the other.
Distinct from the user-producer-oriented methodology, the co-occurrence of classification codes within a patent document is employed to identify the relationship between the knowledge base in different fields. The assumption is that co-occurrence measures the strength of the knowledge link and spillovers between the technological areas.
Jaffe (1986) calculates the distribution of patents over 49 technological fields on a sample of US firms and measures the correlation (angular separation) between the research efforts performed in each innovative area, obtaining the similarity between firms' R&D activities through a cosine index.
Following Jaffe (1986), we calculate the distance between cluster centroids in the technological space defined above (Figure 3) and employ it as a proxy for knowledge relatedness between technological fields.
In order to exploit the cluster-pairwise variation of our dependent variable, we calculate the relatedness ($PROX$) between technological efforts as follows:

$$PROX_{i,t} = \frac{PAT_{ng,t}}{DIST_i}$$

where technological proximity between each couple of clusters (i) is equal to the number of patents in the non-green cluster ($PAT_{ng,t}$) divided by the distance between the centroids of the two clusters ($DIST_i$). This formula allows us to weight the knowledge included in non-green clusters by its similarity to the green one. Therefore, higher distance between two clusters is associated to lower technological similarity (holding distance as constant).
Thus, firms may drive away inventive activities within low cognitive distances which implies that the search process is carried out among similar technological fields. For example, inventive efforts in new promising environmental technological fields may reduce other kinds of technologies that are related to the internal combustion engine (competing technology), rather than decreasing other elements of the powertrain system (i.e., transmissions) that may also be adopted in alternative vehicles.

4.3 Other variables

In addition, we include variables that capture the linkage between clusters knowledge base. In order to hold constant other aspects that may influence the propensity to substitute efforts in two technological fields, we control for the number of citations among technological fields (CIT) and the number of firms that file patents in each couple of clusters (NoF). The former aims to detect the technical relationship between technological domains through a vertical perspective since, when patents are filed at the patent office, they include citations to earlier patents which new patent applications build upon (OECD, 2009). This represents a good indicator of past knowledge used by inventors to exploit inventions (Popp, 2002).

It should be noted that this variable differs from the previous one ($PROX$) in the same way as knowledge similarity differs from knowledge flow. Indeed, whereas the cognitive distance detects proximity among clusters (within the whole dataset), citations identify the extent to which past knowledge embodied in a technological cluster is exploited by others. Hence, the CIT variable is closer to the concept of vertical complementarity and the generation of new knowledge is conditional to the identification and integration of different complementary 'modules' in which recombination assumes a pivotal role (Antonelli, 2003). In this direction, citations track the recombination of pieces of knowledge acquired in the past with recently elaborated ones.

Moreover, we also focus on the current relationship of technological knowledge in different clusters using the number of firms that patent across clusters. We assume that when firms exploit more than one invention in different technological fields, it can be interpreted as a relationship between the knowledge base included in those clusters. The concept of knowledge compositeness is here recalled for interpreting knowledge inter-dependence between technological fields. Knowledge compositeness is defined as the 'variety of units of technological knowledge that are necessary and complementary in the production of a new product or process, as well as of a new unit of knowledge' (Antonelli and Calderini, 2008; p. 24). From the automotive industry perspective, the importance of knowledge compositeness highlights the changes in the technological and scientific advances faced by the industry that no longer resides on single technological fields (Antonelli and Calderini, 2008).

Finally, we include the stock of patents in environmental and non-environmental technological fields (PS). Aghion et al. (2012) highlights that past knowledge impacts the propensity to innovate in green and non-green technologies due to the presence of a lock-in effect.

Following Cockburn and Griliches (1988), Peri (2005) and Aghion et al. (2012), we calculate the stock of patents in each cluster using the perpetual inventory method:

$$PS_{z,t} = PAT_{z,t} + (1-\delta)PS_{z,t-1}$$

where PS is the patent stock in the technological field j and PAT its patent count in each year. Following the related literature, we set the depreciation of R&D capital (δ) at 20%.

5 Results

In this section we present and provide an explanation for the results for both hypotheses tested over the period 1982-2008 (26 years), i.e. green vs. non-green and green vs. green inventive activities. Table 3 shows the descriptive statistics and Table 4 the correlation matrix for both the models.

5.1 Green vs. non-green patents

As far as competition between green vs. non-green inventive activities is concerned, the results of the fixed effects linear model are shown in the first column of Table 5. Independent variables are lagged by one year in order to account for the time to exploit inventions[16], a common practice used in other related studies (Aghion et al., 2012; Lee et al., 2012; Popp and Newell, 2012).

When analysing the results, we observe that an increase in tax-inclusive fuel prices enhances the likelihood that green inventions come at the expense of non-green ones. Since environmental

[16] It should be noted that we collected patents using the earliest priority year in the patent family that indicates the first moment in which firms had applied for the patent at any patent office. This is the closest date to the end of the invention process and therefore we do not need to include additional lags to account for the patent office administrative time (another 18 months on average to publish the patent application).

regulations trigger environmental automotive inventive efforts (Aghion et al., 2012; Lee et al., 2012; Hascic et al., 2009), the results seem to provide evidence that firms tend to reallocate R&D resources from non-green to green investments due to the need to comply with policy requirements. This result can be interpreted as an insight that post-tax fuel prices impact competition between the two technological fields and contribute to crowding out ICEVs inventive activities in favour of alternatively propelled vehicle technologies. Therefore, on the one hand, we advocate that environmental regulation is effective in unlocking the automotive technological system from path dependence on conventional vehicle innovation. Higher fuel prices encourage firms to carry out environmental inventive activities while discouraging dirty invention development (Aghion et al., 2012). On the other hand, an increase in environmental policy stringency hampers non-environmental patent efforts and thus the social benefit that arises from new eco-innovation.

Other remarks can be extrapolated from the proximity variable. The coefficient indicates that the greater the dissimilarity between technological clusters (i.e. distant cluster in the technological space), the lower the shift from non-environmental to environmental inventive activities. Thus, we point out that firms have a tendency to reduce efforts in the technological clusters that are closer (i.e. related in terms of CPC classes) to the green ones. From Figure 3, we observe that more distant technological clusters (the upper side of the map) with respect to green clusters, are not directly related to internal combustion engines. This issue highlights the fact that, when holding constant other variables, firms' patent strategies are directed towards increasing efforts in environmental technologies at the expense of non-green inventions such as conventional engines, or alternatively, that this effect is lower for those clusters that are more distant in the technological space. This result confirms the abovementioned competition between the main technological trajectories in the automotive industry. The efforts made in these alternative powered engines (such as hybrid, electric and fuel cell), compete with inventions directly related to fossil fuel engines rather than with technologies that can also be adopted in alternative cars, i.e. safety, transmission, brake technologies and tyres.

5.2 Green vs. green patents

In addition, we investigate the potential effect of environmental policy on competition between green technologies. This issue is fundamental to testing whether green inventions drive away inventive efforts from other green fields due to policy stringency or other factors that influence technological competition. In so doing, we account for the effect of each green technological cluster on the others included in the green domain. From Table 5 column 2, we can observe that the environmental policy coefficient is positive and significant. This means that there are insights that tax-inclusive fuel prices impact competition between alternative technological advances. Therefore, this issue highlights that environmental policies may redirect technological efforts towards other environmental domains increasing the likelihood of a potential lock-in into sub-optimal alternative technology. Indeed, instead of inducing improvements in a particular technological field, tax-inclusive fuel prices should encourage firms to exploit a variety of technological trajectories (Frenken et al., 2004) because, at the current stage of technological advances in low emission vehicles, it is hard to assess whether an alternative technology is superior to the others. For example, even though fuel cell vehicles are considered the most promising technology compared with hybrid and electric cars, important bottlenecks must be solved and therefore the risk of lock-in into a technology which may turn out to be sub-optimal in the future remains (Frenken et al., 2004).

In this regard, we provide a suggestive interpretation of these results by categorising the clusters within four main groups. As stated in Section 3.3, the main trajectories that characterise green R&D efforts are end-of-pipe technologies, HVs, EVs and FCVs. Following Popp and Newell (2012), Table 6 shows the correlation between the percentage of patents per year in each category among three time ranges. We can observe that the highest negative correlation is between end-of-pipe technologies and other vehicle propulsion technologies in all time ranges. This issue provides insights that competition between green patenting activities mainly regards these two broad categories of technological efforts i.e. end-of-pipe vs. EVs, HVs and FCVs. Thus, even within the environmental technological domain, the competition between the two vehicle designs characterises the technology space.

Moreover, the proximity variable is positive and statistically insignificant meaning that technological relatedness among the technology space does not influence the shift from green to other green technological efforts. Indeed, firms respond to technological opportunities that are constantly being proposed by technological advances, highlighting the absence of a dominant technology among alternatives to fossil fuel engine. Therefore, due to the fact that environmental patenting efforts are made in a variety of technological fields, the dynamic changes in these technological trajectories induce firms to invest in a portfolio of environmentally friendly technologies that face higher technological opportunities at that moment. However, in this case, the similarity between technological activities does not impact the shift from one technological field to the other.

5.3 Robustness checks

In this Section we provide some robustness checks to assess the reliability of the model results using different variables. Table 7 shows the results employing a 3, 4, 5 year patent count moving average as dependent variable. Previously, a 4-year moving average was used to provide the main results, although we can observe that coefficient signs and their significance are almost the same using different dependent variables in both models, at least as far as the main independent variables are concerned.

Moreover, we run the model using a different proxy for the environmental policy variable (Table 8). Whereas results in Table 5 are obtained using tax-inclusive fuel prices in three main countries (i.e. EU, JP and US), Table 8 shows the model results using the whole set of countries in each cluster[17] (EP_all). This variable is obtained by calculating the share of patents from each country of origin in each cluster, multiplied by the tax-inclusive fuel price of each country. Again, the coefficient signs and significance are almost the same using the two variables.

Finally, Table 9 shows the results using fuel taxes instead of tax-inclusive fuel prices. However, due to the availability of fuel tax data, the period of study is reduced (1986-2008). Also in this case the models show similar results to those obtained using tax-inclusive fuel prices. This result provides an insight into fuel tax effectiveness in fostering competition between alternatives.

6 Conclusions

In this paper we have analysed the dynamics of inventive activities pursued by large automotive firms with a specific focus on the role played by environmental policies in influencing competition between conventional (ICE) and low-emission vehicle technologies.

Our findings suggest that tax-inclusive fuel prices, employed as a proxy for carbon tax, induce a shift from non-environmental inventive efforts towards those related to the development of alternative vehicles and we have provided insights that environmental regulation encourages a crowding out effect that favours substitution instead of complementarity among inventive efforts. Therefore, we have highlighted the effectiveness of regulation in unlocking the automotive technological system from fossil fuel path dependent technologies.

[17] AT, DE, FR, IT, JP, KR, SE, UK, US

What is more, together with environmental policy, other factors affect competition. In particular, the technological similarity between green and non-green clusters assumes a pivotal role. The fact that technological relatedness positively impacts the shift from non-green to green inventions is confirmed. Indeed, environmental technologies related to hybrid, electric and fuel cell vehicles compete with internal combustion engine technologies that are close to them in the technological space. Therefore, substitution mainly affects close technologies, such as propulsion system technologies, rather than complementary technologies such as transmissions, body design, tires and safety systems.

Finally, the hypothesis that environmental policies may impact competition between alternative technological efforts has been tested. The results seem to provide evidence that tax-inclusive fuel prices affect competition between environmental technological domains. This issue may increase the risk of lock-in into suboptimal substituting vehicle technologies mainly due to the fact that, at the current stage of development in alternative technologies, the community of technologists is unable to identify a best alternative to internal combustion engine vehicles. In addition, we have observed that this effect regards green inventive activities and environmental technologies related to fossil fuel vehicles. Indeed, even within the environmental technological domain there is competition between low-emission vehicle technologies and the greening of conventional design. However, further investigation is needed to assess the direction of this potential shift. That is, if alternative vehicle inventions crowd out technological efforts that reduce the environmental impact of conventional cars, the likelihood of unlocking the automotive industry from fossil fuel path dependence would be increased. Otherwise, driving away inventive efforts from long run (development of alternative powertrain systems) to short run technological solutions (catalytic converters, improved efficiency of conventional engines, etc.) would hamper the capability of the automotive industry to escape internal combustion engine lock-in.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The Environment and Directed Technical Change. The American Economic Review, 102(1), 131-166.

Aghion, P., Dechezlepretre, A., Hemous, D., Martin, R., and Reenen, J. V. (2012). Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry. Working Paper 18596, National Bureau of Economic Research.

Antonelli, C. (2003). Knowledge complementarity and fungeability: implications for regional strategy. Regional Studies, 37(6-7), 595-606.

Antonelli, C., & Calderini, M. (2008). The governance of knowledge compositeness and technological performance: the case of the automotive industry in Europe. Economics of Innovation and New Technology, 17(1-2), 23-41.

Armand, M., & Tarascon, J. M. (2008). Building better batteries. Nature, 451(7179), 652-657.

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. The economic journal, 116-131.

Basalla, G. (Ed.). (1988). The evolution of technology. Cambridge University Press.

Bergek, A., Berggren, C., & KITE Research Group. (2014). The impact of environmental policy instruments on innovation: A review of energy and automotive industry studies. Ecological Economics, 106, 112-123.

Boschma, R. (2005). Proximity and innovation: a critical assessment. Regional studies, 39(1), 61-74

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. Research Policy, 32(1), 69-87.

Bruckner, E., Ebeling, W., Montaño, M. J., & Scharnhorst, A. (1996). Nonlinear stochastic effects of substitution - an evolutionary approach. Journal of Evolutionary Economics, 6(1), 1-30.

Cecere, G., Corrocher, N., Gossart, C., & Ozman, M. (2014). Lock-in and path dependence: an evolutionary approach to eco-innovations. Journal of Evolutionary Economics, 24(5), 1037-1065.

Cockburn, I., & Griliches, Z. (1988). Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents. The American Economic Review, 419-423.

Cohen, W. M., & Klepper, S. (1996). A reprise of size and R & D. The Economic Journal, 925-951.

Costantini, V., Crespi, F., & Curci, Y. (2013). BioPat: An Investigation Tool for Analysis of Industry Evolution, Technological Paths and Policy Impact in the Biofuels Sector. In The Dynamics of Environmental and Economic Systems (pp. 203-226). Springer Netherlands.

Cowan, R., & Hultén, S. (1996). Escaping lock-in: the case of the electric vehicle. Technological forecasting and social change, 53(1), 61-79.

Crabb, J. M., & Johnson, D. K. (2007). Fueling the Innovative Process: Oil Prices and Induced Innovation in Automotive Energy-Efficient Technology. Technical report, Colorado College Department of Economics and Business, Colorado Springs, CO.

David, P. A. (1985). Clio and the Economics of QWERTY. The American economic review, 332-337.

Davies, D. L., & Bouldin, D. W. (1979). A cluster separation measure. Pattern Analysis and Machine Intelligence, IEEE Transactions on, (2), 224-227.

Dernis, H. and M. Khan (2004), "Triadic Patent Families Methodology", OECD Science, Technology and Industry Working Papers, 2004/02, OECD Publishing. http://dx.doi.org/10.1787/443844125004

Dijk, M., & Yarime, M. (2010). The emergence of hybrid-electric cars: innovation path creation through co-evolution of supply and demand. Technological Forecasting and Social Change, 77(8), 1371-1390.

Faber, A., & Frenken, K. (2009). Models in evolutionary economics and environmental policy: Towards an evolutionary environmental economics. Technological Forecasting and Social Change, 76(4), 462-470.

Frenken, K., Hekkert, M., & Godfroij, P. (2004). R&D portfolios in environmentally friendly automotive propulsion: variety, competition and policy implications. Technological Forecasting and Social Change, 71(5), 485-507.

Gelijns, A. C., Zivin, J. G., & Nelson, R. R. (2001). Uncertainty and technological change in medicine. Journal of Health Politics, Policy and Law, 26(5), 913-924.

Gray, W. B., & Shadbegian, R. J. (1998). Environmental regulation, investment timing, and technology choice. The Journal of Industrial Economics, 46(2), 235-256.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature, 1661-1707.

Hascic I., de Vries F., Johnstone N. and Medhi N., (2009). Effects of environmental policy on the type of innovation: The case of automotive emission-control technologies. OECD Journal: Economic Studies. OECD Publishing, vol. 2009(1), pages 1-18.

Hottenrott, H., & Rexhäuser, S. (2013). Policy-induced environmental technology and inventive efforts: Is there a crowding out? (No. 128). DICE Discussion Paper.

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. The American Economic Review, 76(5), 984-1001.

Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2002). Environmental policy and technological change. Environmental and resource economics, 22(1-2), 41-70.

Kohonen, T. (1990). The self-organizing map. Proceedings of the IEEE, 78(9), 1464-1480.

Kohonen, T. (2001). Self-organizing maps (Vol. 30). Springer Science & Business Media.

Kohonen, T. (2013). Essentials of the self-organizing map. Neural Networks, 37, 52-65.

Kneller, R., & Manderson, E. (2012). Environmental regulations and innovation activity in UK manufacturing industries. Resource and Energy Economics, 34(2), 211-235.

Lanjouw, J. O., Pakes, A., & Putnam, J. (1998). How to count patents and value intellectual property: The uses of patent renewal and application data. The Journal of Industrial Economics, 46(4), 405-432.

Laperche, B., Lefebvre, G., & Langlet, D. (2011). Innovation strategies of industrial groups in the global crisis: Rationalization and new paths. Technological forecasting and social change, 78(8), 1319-1331.

Lee, J., Veloso, F. M., & Hounshell, D. A. (2011). Linking induced technological change, and environmental regulation: Evidence from patenting in the US auto industry. Research Policy, 40(9), 1240-1252

Leydesdorff, L., Alkemade, F., Heimeriks, G., & Hoekstra, R. (2014). Patents as instruments for exploring innovation dynamics: geographic and technological perspectives on “photovoltaic cells”. Scientometrics, 1-23.

MacQueen J. B. (1967). Some methods for classification and analysis of multivariate observations.In Proceedings of 5th Berkeley symposium on mathematical statistics and probability, pp. 281–297.

Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., & Beardsley, G. (1977). Social and private rates of return from industrial innovations*. The Quarterly Journal of Economics, 221-240.

Marin, G. (2014). Do Eco-Innovations harm productivity growth through crowding out? Results of an extended CDM model for Italy. Research Policy, 43(2), 301-317.

Nelson, R.R. and Winter, S.G. (1982). An evolutionary theory of economic change. Cambridge Mass: Harvard University Press.

Nesta, L., & Saviotti, P. P. (2005). Coherence of the knowledge base and the firm's innovative performance: evidence from the us pharmaceutical industry. The Journal of Industrial Economics, 53(1), 123-142.

OECD (2009), Patent Statistics Manual, OECD, Paris.

Oltra, V., & Saint Jean, M. (2009). Variety of technological trajectories in low emission vehicles (LEVs): a patent data analysis. Journal of Cleaner Production, 17(2), 201-213.

Pakes, A. (1985). On Patents, R & D, and the Stock Market Rate of Return. The Journal of Political Economy, 390-409.

Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. Review of Economics and Statistics, 87(2), 308-322.

Popp, D. (2002). Induced Innovation and Energy Prices. American Economic Review, 92(1), 160-180.

Popp, D. (2005). Lessons from patents: using patents to measure technological change in environmental models. Ecological Economics, 54(2), 209-226.

Popp, D., Newell, R. G., & Jaffe, A. B. (2010). Energy, the Environment, and Technological Change. Handbook of the Economics of Innovation, 2, 873-937.

Popp, D., & Newell, R. (2012). Where does energy R&D come from? Examining crowding out from energy R&D. Energy Economics, 34(4), 980-991.

Porter, M. E., & Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. Journal of economic perspectives, 9, 97-118.

Rennings, K., Markewitz, P., & Vögele, S. (2013). How clean is clean? Incremental versus radical technological change in coal-fired power plants. Journal of Evolutionary Economics, 23(2), 331-355.

Scherer, F. M. (1982). Inter-industry technology flows in the United States. Research policy, 11(4), 227-245.

Vesanto J. (1999). SOM-based data visualisation methods. Intelligent Data Analysis, vol. 3, pp. 111-126.

van den Bergh, J. C. (2013). Environmental and climate innovation: Limitations, policies and prices. Technological Forecasting and Social Change, 80(1), 11-23.

Thoma, G., Torrisi, S., Gambardella, A., Guellec, D., Hall, B. H., & Harhoff, D. (2010). Harmonizing and combining large datasets–an application to firm-level patent and accounting data (No. w15851). National Bureau of Economic Research.

Figures

Figure 1 – Green and non-green patent trends and percentage of green patents over total yearly patents

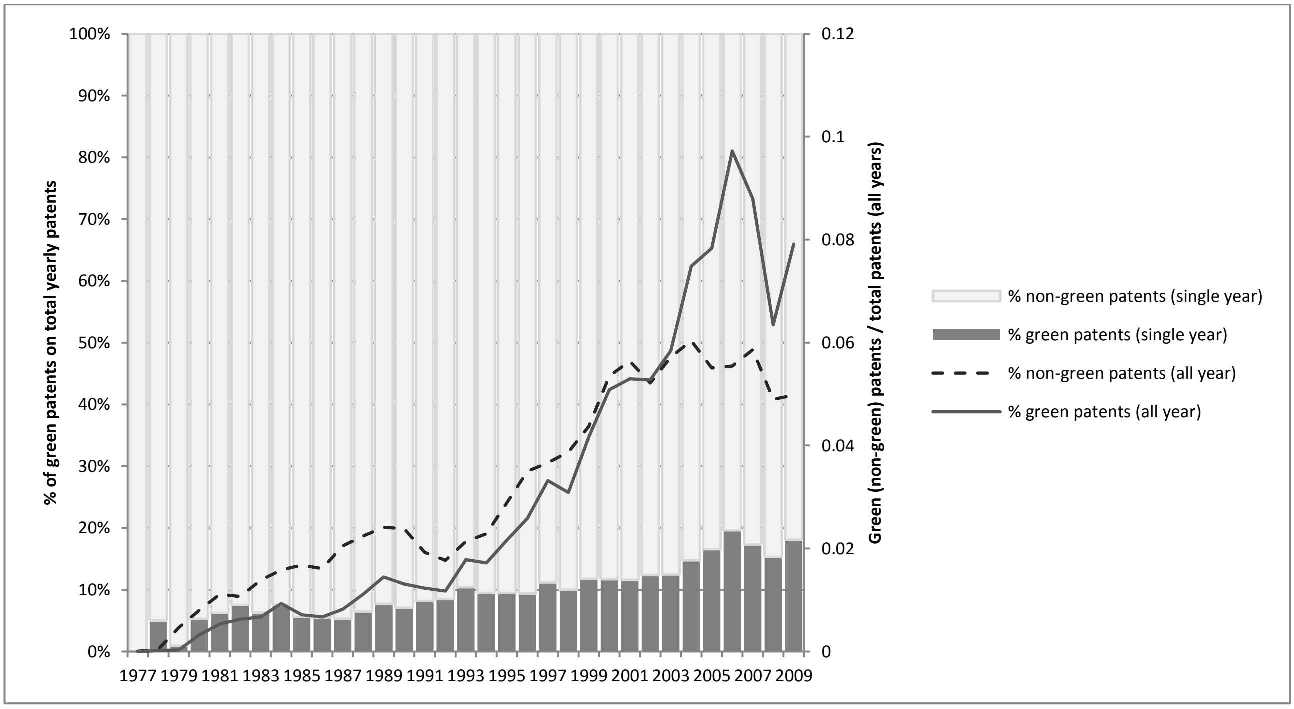


Figure 2 – Steps of SOM algorithm

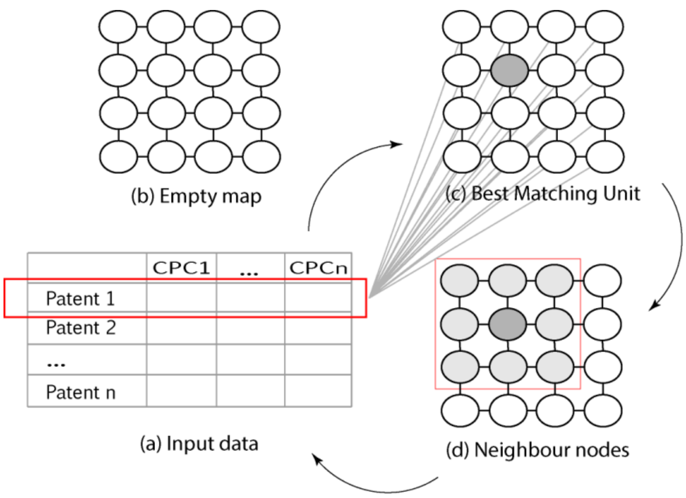
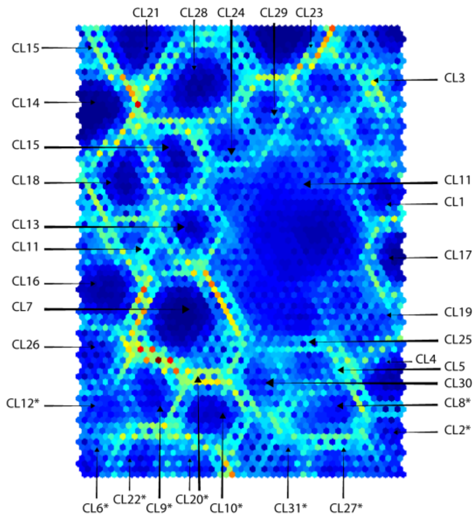


Figure 3 – Unified-distance matrix and clustering results

a)



b)

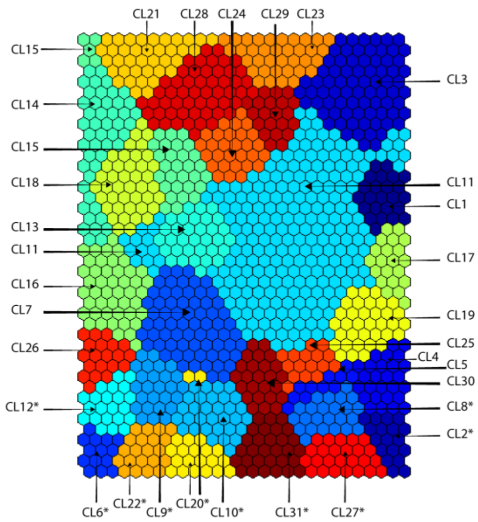
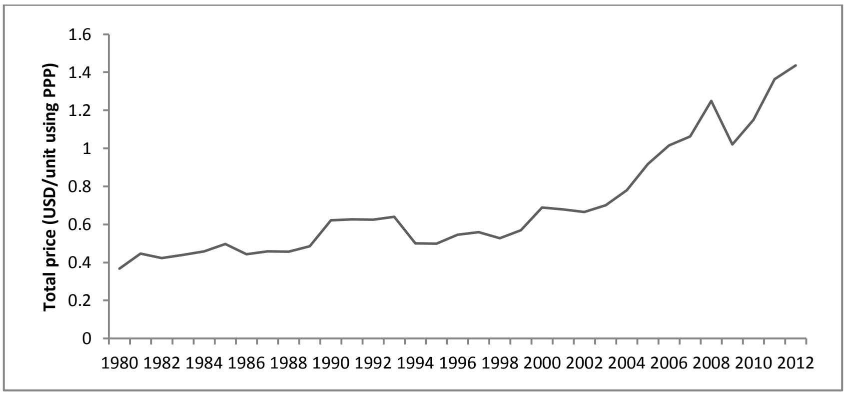


Figure 4 – Average post-tax fuel price between premium unleaded 95 RON and diesel in OECD countries



Source: Own figure using data from IEA

Tables

Table 1 – Description of clusters

CL	Keywords	# of patents	% of green patents
1	Bore, crank, pistons	760	0,00
2	**Ignition, catalyst, throttle**	**1455**	**100,00**
3	Tyre, rubber, pneumatics	5328	1,33
4	Injector, spark, crank	1640	0,00
5	NOx, SOx, particulate	98	0,00
6	**Battery, hybrid, regeneration**	**699**	**99,86**
7	Cell, cathode, anode	1598	0,31
8	**NOx, catalyst, purification**	**514**	**98,25**
9	**Gear, stator, transmission**	**174**	**100,00**
10	**Spark, battery, octane**	**347**	**100,00**
11	Wiper, door, antenna	18568	0,15
12	**Transmission, gear, hybrid**	**359**	**99,44**
13	Stator, pole, rotor	882	0,68
14	Transmission, pulley, hydraulic	2864	1,26
15	Caliper, friction, brake	1330	0,90
16	Pointer, drowsiness, menu	1091	0,00
17	Injector, nozzle, carburetor	1673	7,23
18	Rubber, etch, windscreen	1076	0,37
19	Camshaft, rocker, crankcase	1445	0,14
20	**Hydrogen, electrolyte, cell**	**525**	**100,00**
21	Brake, master, skid	2047	0,64
22	**Battery, charger, PLC**	**502**	**99,60**
23	Airbag, inflate, retractor	2841	0,32
24	Suspensions, strut, axle	1001	0,00
25	Muffler, catalyst, silencer	357	0,00
26	Cruise, yaw, headway	604	0,00
27	**Turbocharger, supercharger, swirl**	**1115**	**100,00**
28	Robot, crawler, roof	1758	0,23
29	Rubber, flywheel, diaphragm	571	0,00
30	Oxide, palladium, acid	328	0,00
31	**Catalyst, NOx, purification**	**820**	**100,00**
	Total	54370	12,52

Table 3 – Descriptive statistics

Gr. vs. Non-Gr

Variable	Obs	Mean	Std. Dev.	Min	Max
CO	*5670*	*-2.233774*	*11.27849*	*-80.25*	*43*
EP (t-1)	*5670*	*1.037521*	*.4561879*	*.1190692*	*2.337916*
PROX (t-1)	*5670*	*71.1831*	*161.6976*	*0*	*2412.939*
CIT (t-1)	*5670*	*.9640212*	*4.023495*	*0*	*82*
F (t-1)	*5670*	*3.183774*	*2.92954*	*0*	*18*
PS ng (t-1)	*5670*	*287.1834*	*579.0677*	*0*	*4769.544*
PS g (t-1)	*5670*	*68.0297*	*83.43386*	*0*	*478.0059*

Gr. vs. Gr

Variable	Obs	Mean	Std. Dev.	Min	Max
CO	*2430*	*2.834568*	*3.325596*	*0*	*24*
EP (t-1)	*2430*	*1.00259*	*.4640165*	*.1162741*	*2.200845*
PROX (t-1)	*2430*	*38.94946*	*87.48263*	*0*	*1050.328*
CIT (t-1)	*2430*	*2.453498*	*7.494261*	*0*	*98*
F (t-1)	*2430*	*2.394239*	*2.485058*	*0*	*12*
PS g (t-1)	*2430*	*68.0297*	*83.44367*	*0*	*478.0059*

Table 4 – Correlation matrix

Gr. vs. Non-Gr						
Variable	**1**	**2**	**3**	**4**	**5**	**6**
EP (t-1)	*1*					
PROX (t-1)	*0.2137*	*1*				
CIT (t-1)	*0.0662*	*0.2000*	*1*			
NoF (t-1)	*0.6039*	*0.3861*	*0.2257*	*1*		
PS ng (t-1)	*0.2808*	*0.9053*	*0.1512*	*0.4451*	*1*	
PS g (t-1)	*0.6853*	*0.1352*	*0.1465*	*0.7121*	*0.2074*	*1*
Gr. vs. Gr						
Variable	**1**	**2**	**3**	**4**	**5**	**6**
EP (t-1)	*1*					
PROX (t-1)	*0.3274*	*1*				
CIT (t-1)	*0.1413*	*0.4954*	*1*			
NoF (t-1)	*0.6954*	*0.5741*	*0.3592*	*1*		
PS g1 (t-1)	*0.6758*	*0.5881*	*0.2118*	*0.7287*	*1*	
PS g2 (t-1)	*0.6758*	*0.3728*	*0.2094*	*0.7287*	*0.4801*	*1*

Table 5 – Main results of fixed-effects linear model

	(1) Gr vs. non-Gr	(2) Gr. vs. Gr.
EP (t-1)	3.1682***	0.6117**
	(0.5538)	(0.2859)
PROX (t-1)	-0.2224***	0.0008
	(0.0126)	(0.0028)
CIT (t-1)	-0.1062*	-0.0266**
	(0.0627)	(0.0108)
NoF (t-1)	0.0189	-0.0010
	(0.0978)	(0.0652)
PS g (t-1)[a]	0.0924***	0.0162***
	(0.0039)	(0.0038)
PS ng (t-1)	-0.0091*	0.0175***
	(0.0046)	(0.0032)
_cons	490.1122	312.9676
	(512.3644)	(326.4627)
N	5670	2430
r2	0.4450	0.4485
F	9.0944	11.6531

The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: 4-years moving average.

[a] In the first column the patent stock is calculated on green and non-green clusters. In the second column, even if we maintained same variable names, the clusters are both green.

*Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table 6 – Correlation between percentage of patents per year in each environmental inventive activity.

Correlation matrix 1986-1993	*End-of-pipe*	*EV*	*HV*	*FCV*
End-of-pipe	*1.00*			
EV	*-0.92* *(0.00)*	*1.00*		
HV	*-0.01* *(0.99)*	*-0.35* *(0.39)*	*1.00*	
FCV	*-0.25* *(0.54)*	*0.08* *(0.86)*	*0.04* *(0.93)*	*1.00*
Correlation matrix 1994-2001				
End-of-pipe	*1.00*			
EV	*-0.02* *(0.97)*	*1.00*		
HV	*-0.79* *(0.02)*	*-0.42* *(0.30)*	*1.00*	
FCV	*-0.63* *(0.09)*	*-0.53* *(0.18)*	*0.51* *(0.20)*	*1.00*
Correlation matrix 2002-2009				
End-of-pipe	*1.00*			
EV	*-0.71* *(0.05)*	*1.00*		
HV	*-0.36* *(0.39)*	*-0.31* *(0.45)*	*1.00*	
FCV	*-0.70* *(0.05)*	*0.20* *(0.64)*	*0.30* *(0.48)*	*1.00*

Table 7 – Model results using different moving averages (3, 4, 5 years)

	Gr vs. non-Gr			Gr vs. Gr		
	3 Years MA	4 Years MA	5 Years MA	3 Years MA	4 Years MA	5 Years MA
EP (t-1)	2.2945***	3.1682***	4.4813***	0.9014**	0.6117**	-0.1426
	(0.6071)	(0.5538)	(0.5140)	(0.3504)	(0.2859)	(0.2344)
PROX (t-1)	-0.2438***	-0.2224***	-0.1914***	0.0000	0.0008	0.0064***
	(0.0127)	(0.0126)	(0.0107)	(0.0035)	(0.0028)	(0.0023)
CIT (t-1)	-0.1447**	-0.1062*	-0.0773	0.0018	-0.0266**	-0.0128
	(0.0706)	(0.0627)	(0.0530)	(0.0138)	(0.0108)	(0.0100)
NoF (t-1)	0.0583	0.0189	0.0328	-0.0640	-0.0010	0.0361
	(0.1105)	(0.0978)	(0.0837)	(0.0782)	(0.0652)	(0.0510)
PS g (t-1)	0.1175***	0.0924***	0.0681***	0.0138***	0.0162***	0.0067**
	(0.0038)	(0.0039)	(0.0039)	(0.0050)	(0.0038)	(0.0033)
PS ng (t-1)	-0.0273***	-0.0091*	-0.0011	0.0137***	0.0175***	0.0114***
	(0.0049)	(0.0046)	(0.0036)	(0.0044)	(0.0032)	(0.0031)
_cons	379.5873	490.1122	343.6314	-50.0743	312.9676	192.1476
	(475.8532)	(512.3644)	(329.6404)	(231.8723)	(326.4627)	(195.2385)
N	5670	5670	5670	2430	2430	2430
r2	0.4558	0.4450	0.4331	0.3575	0.4485	0.3868
F	6.7908	9.0944	12.2547	9.3342	11.6531	11.1085

*The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: 3, 4, 5 years moving average. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01*

Table 8 – Model results using a different policy variable

	Gr vs. Non Gr	Gr. vs. Gr
EP_all (t-1)	3.2838***	0.6573**
	(0.5533)	(0.2817)
PROX (t-1)	-0.2224***	0.0008
	(0.0126)	(0.0028)
CIT (t-1)	-0.1053*	-0.0264**
	(0.0627)	(0.0108)
NoF (t-1)	0.0223	0.0008
	(0.0977)	(0.0651)
PS g (t-1)	0.0924***	0.0160***
	(0.0039)	(0.0038)
PS ng (t-1)	-0.0101**	0.0174***
	(0.0047)	(0.0032)
_cons	473.3723	311.8109
	(511.7267)	(326.1725)
N	5670	2430
r2	0.4452	0.4486
F	9.0745	11.6255

*The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: 4-years moving average. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01*

Table 9 – Main results of fixed-effects linear model using fuel taxes as policy variable (1986-2008)

	(1) Gr vs. non-Gr		(1) GR vs. Gr	
EP (t-1)	3.0881*** (0.8834)		2.7583*** (0.5844)	
ET (t-1)		11.9629** (5.3684)		12.0665*** (3.5284)
PROX (t-1)	-0.2309*** (0.0132)	-0.2315*** (0.0133)	0.0008 (0.0033)	-0.0007 (0.0032)
CIT (t-1)	-0.1197* (0.0649)	-0.1267* (0.0650)	-0.0249** (0.0108)	-0.0279** (0.0109)
NoF (t-1)	0.0389 (0.1017)	-0.0025 (0.1012)	0.0125 (0.0688)	-0.0122 (0.0690)
PS g (t-1)	0.1071*** (0.0040)	0.1084*** (0.0041)	0.0065 (0.0052)	0.0168*** (0.0044)
PS ng (t-1)	-0.0201*** (0.0074)	-0.0030 (0.0055)	0.0082* (0.0043)	0.0175*** (0.0037)
_cons	406.5658 (656.7143)	1294.4763* (731.0743)	-85.1920 (433.4057)	724.8870 (483.1778)
N	4830	4830	2070	2070
r2	0.4970	0.4960	0.4431	0.4399
F	8.2160	8.1272	9.2941	9.4890

*The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: 4-years moving average. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*