Investigating the impacts of technological position and European environmental regulation on green automotive patent activity

Nicolò Barbieri

Abstract: Using patents data on environmental road transport technologies filed by 355 assignees over the period 1999-2010, the paper investigates under what conditions the European environmental transport policy portfolio and the intrinsic characteristics of assignees' knowledge boost worldwide green patent production. The findings suggest that post-tax fuel prices, environmental vehicle taxes, CO2 standards and European emission standards, introduced into the empirical model through an innovative methodology based on Self-Organising Maps (SOM) (Kohonen, 1990; 2001), positively influence the creation of environmental inventions. Most importantly, the paper highlights that assignees anticipate the introduction of regulatory instruments (i.e. European emission standards and CO2 targets) by filing patents before the effective implementation of regulations when legislation is announced. Furthermore, the paper provides evidence that in a technological space (which measures the applicants' technological proximity), closely located assignees enhance their patent output through the exploitation of technological knowledge produced by others. This means that the greater the proximity between assignees, the higher their likelihood of gaining advantage from this potential spillover pool. Finally, the paper observes that dynamic changes in assignees' patent portfolios spur inventive performances.

1 Introduction

In a complex framework such as long-term climate policy analysis, market failures play a pivotal role by threatening the achievement of environmental and innovation objectives. One of these objectives is the development and exploitation of eco-innovation, defined as 'the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (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, 2007; pp.7). However, an absence of interventions by policy makers to create the incentives to internalize and share the costs of pollution encourages firms to pollute too much and innovate too little with respect to the social optimum (Johnstone et al., 2010).

Although the literature on environmental policy-induced innovation has provided evidence that green policy spurs eco-innovation (see Popp et al. (2010) for a detailed survey), environmental regulation is only part of the story. In fact, interacting market failures associated with both environmental pressure and the creation of new technologies may bias policy analysis.

Since those market failures arise from both the negative environmental impact of economic activities and the positive externalities of knowledge creation, the majority of studies lack investigation of what influences technological change from a combined institutional and technological perspective that may fill the gap in the understanding of endogenous technological change[1]. Thus, the study of this dynamic interaction appears important because investments in technological knowledge are exposed to uncertainty, high costs, information asymmetry, and positive externalities (i.e. other firms may benefit without incurring all the development costs) (Jaffe et al., 2005), all of which may reduce innovative performances even if environmental policies have been properly designed.

Using patents as a proxy for invention, the present paper delves into what triggers green invention development. It includes both the European environmental policy portfolio and the intrinsic characteristics of knowledge (i.e. the potential spillover pool and dynamic knowledge compositeness) in the analysis.

To this end, the paper focuses on those automotive technologies that allow for a reduction in the environmental impacts of the road transport sector, this being one of the main sectors most responsible for different environmental externalities (e.g. greenhouse gas (GHG) emissions, etc.) (Timilsina and Dulal, 2011), and one of the major R&D investors in Europe (Ploder, 2011).

This paper makes manifold innovative contributions. First, it 'unpacks the box' of environmental inventions by distinguishing among several sub-fields of inventive activities that compose the environmental patent data set related to passenger cars (see Section 3.1). For this purpose, it employs the so-called Self-Organising Map (SOM) (Kohonen, 1990, 2001). This is an unsupervised Neural Network (NN) technique able to detect similarities in multidimensional data and represent them in a two-dimensional map where an overall order is achieved. That is, through an iterative process, this technique measures the Euclidean distance (ED) between the multidimensional input data and the interconnected lattice of nodes, i.e. the SOM. Once the winning map node (i.e. the node with the lowest ED) has been detected, the learning process creates a map similar to the input data by shrinking the nodes located in the neighbourhood towards the winning node (Kohonen, 2013). Thus, in the output map similar items are placed closer to each other, whereas less similar ones are mapped further away (Kohonen, 2013).

The added value of this methodology is that it makes it possible to create distance-based maps where the patents, assignees, or emission standards are mapped in relation to specific and relative characteristics of their multidimensional input data. That is, the learning process allows each map node to become more similar to the assigned input data. Moreover, the other map nodes move closer to each selected node, undergoing or causing the shrinking of the neighbour nodes.

Most importantly, the distance between the mapped items can be measured, used as a proxy for the similarity of input data and employed in empirical analysis. Indeed, in the first application of this technique patents and their technological classes were employed to build a distance-based patent map that identified the technological domains that characterised the automotive technology space[2]. The distance between patents was then used as a proxy for their technological relatedness in order to obtain clusters of technologies. In the second application, we ran the SOM using as input data the distribution of patents filed by each assignee in each specific

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[1] Popp (2002) and Aghion et al. (2012) are exceptions.

[2] Section 3.1 and Appendix B show the technicalities of the SOM. Appendix C reports the results of the clustering process and the main key words that characterise each cluster.

technological field defined in the previous SOM exercise. The distance among assignees was used as a proxy for the similarity of assignees' knowledge base. Finally, in the third application the input data were maximum thresholds of pollutants allowed by European emission standards and CO2 targets. In this case, the distance among the items mapped was used as a proxy for the stringency of generic regulatory instruments.
Furthermore, we investigated whether assignees are able to anticipate the effective introduction of mandatory environmental policies by developing inventions when regulations are announced.
Finally, we shed light on the effect of European regulation on foreign inventive activities carried out to comply with the European regulatory system. Differently from those studies that investigate innovation diffusion, this paper makes use of 'prior' patents (i.e. earliest patent applications within a patent family whose priority country is European), to test whether the geographical context impacts on assignees' responses to regulatory changes.
The paper is structured as follows: Section 2 presents the literature on both the innovation impact of environmental policy instruments and the knowledge characteristics that spur innovative performances. Section 3 describes the methodological framework through which the independent variables were built. Subsequently, Section 4 introduces the empirical model and Section 5 describes the results. Finally, Section 6 concludes.

2 Theoretical background and provable hypotheses

2.1 Environmental policies and innovation

In recent decades, several scholars have investigated the relationship between environmental policies and technological change, with results that provide evidence of a positive impact of the former on the latter (Green et al., 1994; Porter and Van der Linde, 1995; Kemp, 1997; Rennings, 2000).
Popp et al. (2010) surveyed empirical studies on policy-driven innovation. The results of this branch of literature depend, at least in part, on the kind of data used to proxy innovation and environmental policies, and on the sector analysed. For example, Jaffe and Palmer (1997) found a positive correlation between pollution abatement control expenditures (PACE) (used to proxy regulatory stringency) and R&D spending, but they did not observe any effect of this policy instrument on patent activity. By contrast, Brunnermeier and Cohen (2003) highlighted a positive relationship between green patents and PACE.
In a recent comparative study between the automotive and energy sector, Bergek et al. (2014) have explored whether different environmental policy instruments support different types of innovations. The paper builds upon an environmental policy classification that groups regulations into four main groups. On the one hand, green regulation differs in the prescriptiveness of the instruments, i.e. economic vs. regulatory (mandatory). On the other hand, instruments diverge according to their technological neutrality, i.e. specific or general. Bergek et al. (2014) have observed that general economic instruments (e.g. CO2 taxes, ETS, etc.) boost incremental innovation, while general regulatory instruments (such as emissions regulation) trigger modular innovation. Finally, technology-specific instruments are suitable for spurring the development of radically new technologies.
Economic instruments provide the incentives to adopt and develop environmentally-sound technologies. Such incentives take the form of economic compensation for the avoided social cost of pollution (Bergek et al., 2014). The literature on general economic instruments in the automotive industry has mainly examined the effect of fuel prices on boosting the development of environmental technologies. Aghion et al. (2012) analysed the effect of tax-inclusive fuel prices on patent activities across worldwide firms. The results evidenced a positive relationship between fuel price, used as a proxy for carbon tax, and environmental innovation.
Due to the fact that fiscal policies also comprise environmental taxes other than fuel taxes (i.e. environmental vehicle taxes) (Timilsina and Dulal, 2011), the literature has explored what spurs innovation beyond fuel prices. This class of polices (e.g. registration taxes, purchase taxes and subsidies, etc.) have been scrutinised by Klier and Linn (2012), who discussed the role of such instruments in promoting car registrations and average vehicle CO2 emission rates. While it was found that these taxes had a significant negative effect on new vehicle registration, the analysis provided little evidence on the decrease in long-run vehicle emission rates.
Furthermore, the literature acknowledges that, together with economic instruments, regulatory environmental policies can be implemented to boost technological change. This broad range of regulatory policies influences firms' actions by prescribing specific technological solutions (technology standards), by establishing upper thresholds to emission levels (emission standards), or by imposing maximum limits of emissions per unit of output (performance standards) (Bergek et al., 2014).
In the automotive industry, the main general regulatory instruments are performance-based standards such as fuel economy, CO2 and noxious emission standards. As regards the former, Clerides and Zachariadis (2008) found that the introduction or adoption of more stringent fuel economy standards and fuel prices improved

new-car fuel efficiency. In addition, the authors observed that in Europe and Japan fuel economy standards have a greater impact than fuel prices. In another noteworthy study, Hascic et al. (2009) analysed how fuel prices, emission standards and on-board diagnostic systems of one country affect automotive green patent activities in the others. The results of their study showed that green inventions have been impacted in a greater and more positive way by foreign regulation than by domestic standards.

Lee et al. (2011) underlined the positive effect of US technology-forcing auto emission standards on innovation in the automotive industry between 1970 and 1998. They found a positive effect: i.e. auto makers and components suppliers innovated in advanced-emission control technologies for automobile applications when the unit cost of auto emissions control devices per car increased, depending on the regulatory period.

Despite the presence of several studies discussing the impact of environmental regulatory systems on innovation, there is a need for more complete analyses of the policy framework that should comprise a more detailed environmental policy portfolio. This may yield deeper understanding of single policy impacts on inventive activities. Therefore, the first hypothesis to test is:

Hypothesis 1. *A rise in fuel taxes and environmental vehicle taxes and more stringent mandatory instrument trigger the production of environmentally-friendly technologies.*

Expected policy changes: Most environmental problems are characterised by uncertainty in regard to future environmental impacts and, consequently, how future policies will respond to them (Jaffe et al., 2005). Moreover, various sources of uncertainty impact on the effectiveness of environmental policy. First, the commitment (or credibility) of policy makers in increasing environmental regulation stringency is a first source of uncertainty (Bansal and Gangopadhyay 2005; Mickwitz et al., 2008). This issue may lead to strategic behaviour by firms that may induce the regulator to reduce or postpone tight standards (Lutz et al., 2000; Puller, 2006). Second, economic uncertainty may threaten investment decisions (Pindyck, 2007) and consequently R&D investments. Third, environmental policy uncertainty, mainly characterised by uncertain signals and irreversible investments, may result in investment postponing (Johnstone et al., 2010)

Whereas environmental policy stringency has been analysed in several papers, the effect of policy predictability remains substantially uncharted, at least from an empirical perspective. Lee et al. (2010) highlighted that innovative activities in the American automotive sector quickly subside if new and tighter emission regulations are not announced.

Therefore, when regulations are predictable, actors may anticipate the introduction of the policy instrument due to lower uncertainty. Berggren and Magnusson (2012) highlighted that car makers anticipated CO2 restriction by reducing emissions when the EU legislation was announced (2008) instead of waiting for its implementation (2012-15). In addition, Nicolli et al. (2012) assessed the role of public policies in triggering recycling innovations, and therefore, in supporting the creation of efficient recycling markets. This empirical study, focused on plastic packaging and end-of-life vehicle waste, found a positive relationship between national policy measures and recycling innovations, providing evidence on the ability of inventors to anticipate policy implementation.

The objective of the present paper is to assess whether general regulatory policies, such as CO2 targets and European emission standards, affect environmental patenting activities before their effective implementation. Hence:

Hypothesis 2. *Assignees anticipate the introduction and the tightening of generic regulatory policy instruments (i.e. Emission standards and CO2 targets) by pursuing inventions before the implementation of those instruments, at the time of their announcement.*

Geographical policy impacts: Various studies have questioned whether environmental policies impact on the diffusion of environmentally sound technologies (Lanjouw and Mody, 1996; Popp, 2006; Dechezleprêtre et al., 2009). This branch of the literature has focused on the third stage of technological change (Schumpeter, 1942) in which inventions, after their inclusion in products and processes (innovation), start to be diffused. The majority of these studies have provided clear evidence that absolute environmental policy stringency induces the transfer of green technologies. Only recently, Dechezleprêtre et al. (2012) have underlined the role played by relative regulation stringency on the transfer of environmentally sound technologies between recipient and source countries.

These works have concentrated on the innovative efforts pursued in a specific country and subsequently transferred to foreign countries. Only a few studies (e.g. Hascic et al., 2009) have analysed the direct relationship between domestic environmental regulations and foreign production of environmental patents.

The focus of this research hypothesis is on the development of inventions produced in foreign countries in order to directly comply with European regulations: for example, a Japanese assignee that develops an invention specifically to comply with European emission standards, rather than divulge already disclosed inventions (maybe developed to comply with stricter national regulations) in that market. Therefore, another hypothesis tested in what follows is:

Hypothesis 3. *European environmental policies directly trigger the development of environmental technologies in other geographical areas.*

2.2 Supply-side factors and innovation

Despite environmental policies that impact positively on innovation by imposing a cost on pollution, knowledge externalities arising from the creation of new knowledge may reduce this effect. The public-good nature of new knowledge means that innovating firms can capture only a fraction of the overall benefit generated by an innovation, even if it is protected through patents or other institutions (Jaffe et al., 2005).

In order to explain the differences in firms' innovative environmental activities and to increase the understanding of endogenous technological change, it is necessary to consider the impact of innovation supply-side factors on eco-innovation. The importance of these factors has been highlighted by Popp (2002), in which the links between past and current research on energy-efficiency innovation were analysed. The results showed that the existing base of scientific knowledge, together with energy prices, triggered energy-efficiency innovation. Moreover, Popp accounted for the quality of knowledge stock through patent citations, finding that the usefulness of the available stock of knowledge assumed importance in shaping eco-innovation.

Another paper that combines supply-side factors and environmental policies is Aghion et al. (2012). The authors tested the hypothesis that directed technical change reduces the negative environmental externalities produced by the automotive sector through an increase in inventive efforts pursued by firms, i.e. an increase in tax-inclusive fuel prices stimulates firms to develop clean technologies. Moreover, their framework provided evidence (using aggregate spillover and firms' own stock of inventions) of path dependence in the type of innovation pursued.

This paper adds elements to this literature by exploring how cognitive distance impacts on environmental inventions. Given that people sharing the same knowledge may learn from each other (Boschma, 2005), the knowledge produced by other firms may influence knowledge production if their cognitive bases are close enough to communicate, understand and process it successfully (Boschma and Lambooy, 1999). Indeed, the effective transfer of knowledge requires absorptive capacity, i.e. the ability to recognise, decode and exploit the new knowledge (Cohen and Levinthal, 1990).

In this regard, through the creation of a technology space capturing the similarity among firms' patent outputs, Jaffe (1986) found that R&D productivity had been enhanced by the potential spillover pool, i.e. a pool of firms that had closer positions within the technology space and from which knowledge potentially leaked out.

Following Jaffe (1986), we test the following hypothesis:

Hypothesis 4. *The potential environmental spillover pool, defined as the sum of other assignees' patenting activities weighted by the similarity across time between their inventive activities, positively impacts on the propensity to develop environmental inventions.*

In other words, we hypothesise that the presence of technological inventive efforts (with lower cognitive distance) pursued by other assignees may enable a given assignee to achieve research objectives with less efforts than otherwise (Jaffe, 1986). In order to enlarge on this theoretical issue, in Section 3.2.1 we calculate the proximity between assignees using their past efforts in each technological field. We assume that the closer the similarity between two assignees' knowledge bases over time, the higher the likelihood that their knowledge will prove fruitful in developing new environmental inventions.

Furthermore, due to the fact that technological change no longer characterises a single technological field, knowledge and competences in numerous fields may favour the development of environmental inventions. That is, knowledge compositeness, defined as the variety of technological fields exploited by inventors, influences the rate at which inventions are effectively introduced in the industry (Antonelli and Calderini, 2008). Moreover, firms' innovative performances and their technological diversification are subject to technological opportunities that characterise the industry (Nieto and Quevedo, 2005). In principle, technological opportunities, defined as the potential for technological advances in both general and specific innovative fields (Olsson, 2005), crucially

influence variation within innovation portfolios (at firm and industry levels) and the quantity of innovation pursued.
The literature does not provide a clear answer as to whether firms that change their technological portfolio (by broadening the type and increasing the quantity of inventions) also enhance their abilities to detect and exploit new knowledge. Hence:

Hypothesis 5. *Changes in applicants' knowledge compositeness spur environmental inventive output.*

Figure 1 provides an overview of the theoretical framework described above. It depicts the main hypotheses tested in the paper.

3 Patent data and variables

In order to retrieve information on assignees' inventing performances such as (i) technological field, (ii) technical description, (iii) country in which they are carried out and (iv) when they have been developed, we used patent data as a proxy for invention. Patents are good indicators of innovative efforts because they are usually filed in the earlier stages of the innovative process (Griliches, 1990). Moreover, it has been highlighted that 'the result from patent counts should be interpreted as the effect of an "average" patent rather than considering them as specific innovations' (Popp, 2005; pp. 214). However, it should be borne in mind that (i) not all inventions are patented, (ii) there are differences in the commercial value of patents (some inventions may have little commercial value), and (iii) they sometimes have a weak correlation with R&D expenditure (Popp, 2005). Notwithstanding the presence of such limitations, the exploitation of patent data is widespread in the literature (Popp, 2002; Hascic et al. 2009; Popp, 2006; Lee et al., 2011; Dechezleprêtre et al., 2012; Aghion et al., 2012).
In order to retrieve the patent data set related to environmental road transport technologies, we employed Cooperative Patent Classification (CPC)[3] codes as a proxy for the scope of the inventions. Using the 'Thompson Innovation database', we downloaded the patents pertaining to the class 'Climate change mitigation technologies related to transportation' (Y02T), which comprises green inventions related to the transport sector[4]. This search strategy enables us to focus on the main technological advances that have characterised the automotive technological framework. In recent decades, two main technological paths have been followed by the community of technologists. Technological efforts have been devoted, on the one hand, to improving the environmental performance of conventional vehicle designs through increased efficiency of the internal combustion engine and the treatment of exhaust gases, and on the other, to developing alternative vehicle technologies (electric, hybrid, fuel cells, etc.)[5].

Many scholars have tracked the patterns of technology diffusion using patents filed with different countries a proxy for technology diffusion. These 'duplications' of the original patent are used to identify the countries in which the assignee foresees market opportunities for the invention (Popp, 2005)[6]. The diffusion process is influenced by factors that are different from those that affect invention. Therefore, this study avoids the inclusion of duplicated patents, for two reasons. Firstly, the focus is on inventive processes rather than on the analysis of what drives the diffusion of inventions. Secondly, in order to test Hypothesis 3, we required a set of inventions that were originally developed to comply with the European environmental regulation. Thus, the inclusion of duplicated patents might have biased our results.
In order to track the inventive efforts made to comply with the European policy framework, we collected the entire patent families[7] of all the inventions downloaded. These comprised 236,960 documents including: patent applications in each country, search reports, modified first pages, etc. Considering only patent applications, for each patent family we obtained the earliest priority year, and for each we identified the 'prior patent'. Subsequently, if this prior patent was filed with any of the European patent offices,[8] we included it in our dataset. The final result was a dataset that, after considering co-patenting[9] and removing observations with missing values (some of the patents had no assignee name, application country, etc.), accounted for 28,900

[3] The patent classification systems assign one or more technological classes to each invention according to its technological fields. These are hierarchical language-independent codes used as proxies for the scope of the invention.

[4] A detailed description of the subclasses is provided in Appendix A.

[5] However, to be noted is that vehicle environmental impact reduction can be also achieved through, for example, vehicle body design that reduces aerodynamic resistance or increases weight saving. This improvements do not directly refer to specific technologies. Therefore, because the main objective of these changes in vehicle design may not be directed to improve vehicle environmental performance, they are not included in our analysis.

[6] For example, if a patent is firstly filed in Japan and a few years later in Germany, this means that the assignee considers Germany as a second potential market for its invention.

[7] Patent families are collections of all the patents that refer to the same invention.

[8] European Patent Office (EPO), AT, BE, BG, HR, CY, CZ, DK, EE, FI, FR, DE, GR, HU, IE, IT, LV, LT, LU, MT, NL, PL, PT, RO, SK, SI, ES, SE, GB

[9] Some patents are developed jointly by more than one assignee. We considered a co-patented invention as a single patent for each assignee.

patents. The final number of assignees that filed more than 2 patents over the period 1999-2010 with no missing information (e.g. address) was 355.

3.1 Using SOM to unpack the "box" of environmental inventions

From a technological point of view, firms involved in competitive markets try to occupy the best position in a technological space relative to their competitors by developing a portfolio of inventions that enables them to achieve this result. This position is characterised by a vector $\mathrm{F} = (\mathrm{F}_1 \ldots \mathrm{F}_\mathrm{k})$ where F_k is the firms' efforts devoted to the k-th technological area (Jaffe, 1986).
Knowledge diversification impacts on the technological position of the firm in the technological space. Thus, placing all the assignees in this space allows us to measure the cognitive distance between them and find assignees that have carried out more similar inventive activities; i.e. assignees are located closer if their research activities are similar and distant from each other otherwise.
To define the k technological fields, we used an unsupervised neural network (NN) technique named Self-Organising Map (SOM) (Kohonen, 1990; 2001). The SOM is a two-layer competitive NN that represents multidimensional data in a two-dimensional topological grid (Kohonen, 2001). This technique is a nonlinearity projecting mapping in which the input data become spatially and globally ordered relatively to the similarity that the process finds within the input data (Kohonen, 2013).
The SOM' algorithm (detailed in Appendix B) maps the input data in a two-dimensional grid, in which the distance between the items can be used as a proxy for relatedness between them. Therefore, similar (different) input data are placed closer (more distant) in the final output map.
In this first application of the SOM, we created a patent map (PM) using co-classification of 8-digit CPC classes assigned to each patent. The assumption was that the presence of the same CPC classes in two patents can be used as a proxy for the strength of the patents' technological relatedness.
Whereas in other studies patent classification co-occurrences are used to measure the relatedness between technological fields (Breschi et al., 2003; Nesta and Saviotti, 2005), we used them to identify the similarity between patents' technological content. In this case, the input data of the SOM in each column was the frequency of 8-digit CPC classes assigned to each patent, while the patent IDs were in the rows:

	CPC 1	CPC 2	…	CPC m
Patent 1	…	…	…	…
Patent 2	…	…	…	…
…	…	…	…	…
Patent n	…	…	…	…

The advantage of applying the SOM with input data of this kind is that it enables detection of technological similarities between patents by calculating their distance in the patent map (PM). The output of the SOM (Figure 2) is a PM where the patents that provide similar (different) technological improvements are placed closer (more distant) (exemplified in Figure 3). Finally, using a k-means algorithm (MacQueen, 1967), we detected 21 technological clusters[10], to which each patent was assigned through the SOM (Figure 4)[11].

3.2 Supply-side variables

3.2.1 The potential spillover pool

Once the k technological areas had been identified, we ran the SOM to obtain the similarities across assignees' innovative efforts. In this second application, the neural network located the assignees in the technology space, a two-dimensional grid of neurons (nodes), where each of them was placed in relation to its patent distribution over the k technological fields. Thus, within this space, assignees with similar research activities were mapped closer than those carrying out very different innovative efforts (placed farther away).
The input data for this application were the numbers of patents filed in each k technological field in columns and, as the observation units, the assignees:

[10] The k-means is run multiple times for each k. The process selects the best alternative with respect to the sum of squared errors. Finally, the Davies-Bouldin index is calculated for each alternative (Davies and Bouldin, 1979).
[11] See Appendix C for a detailed description of the clusters' contents.

	Battery	Intern combustion	…	Technological field m
Assignee 1	…	…	…	…
Assignee 2	…	…	…	…
…	…	…	…	…
Assignee n	…	…	…	…

However, in order to identify the similarity between assignees' knowledge over time, we ran the SOM employing as input data the assignees' stocks of patents in each technological field calculated through the perpetual inventory method (Cockburn and Griliches, 1988; Peri, 2005; Aghion et al., 2012):

$$SPAT_{s,k,t} = NPAT_{s,k,t} + (1-\delta)SPAT_{s,k,t-1}$$

where, $SPAT$ is the patent stock in each technological field (k) and $NPAT$ is the number of patents filed at time t in the field k by assignee s. Finally, the depreciation parameter of R&D (δ) was set at 20%, a common practice in the related literature. Consequently, on measuring the distance between two firms, and therefore between two neurons on the map, we obtained a new measure of distance that we used as a proxy for the cognitive distance between them, reflecting the similarity between their knowledge bases over time. Hence, two assignees with identical patent portfolios were located in the same neuron; otherwise, perfectly orthogonal vectors were further away. Finally, we measured the potential spillover pool (PSP) for firm i at time t as follows:

$$PSP_{i,t} = \sum_{j \neq i = 1}^{s} \frac{EPAT_{j,t}}{DIST_{i\,j}}$$

$$j + i = s$$

where $EPAT_{j,t}$ are environmental patents filed by another assignee j at time t. $DIST_{i\,j}$ is the distance on the map between the two assignees using $SPAT$ as input data. Finally, s is the total number of assignees. In this way, the potential stock of external knowledge that arises from the potential spillover pool, that is available for i, increases when the patent count of j increases, and decreases when their proximity in the knowledge space decreases[12]. As posited by Breschi et al. (2003), there are several measures that can be applied to assess this cognitive distance between firms' research activities (Scherer, 1982; Verspagen, 1997; to cite a few). The choice of using SOM is due to its ability to reach a local and global order within the map. It does not provide a similarity measure between pairs of objects, but rather between all the observations in the dataset[13].

3.2.2 Dynamic knowledge compositeness

The SOM is also useful for defining the dynamic patterns that characterise assignees' positions in the technology space. To measure the changes in an applicant's knowledge compositeness, we tracked the firms' movements within the technology space. Those movements are caused by changes in the type and quantity of inventions in each technological field characterising the environmental patent portfolios of assignees.

Note that an applicant's position on the map is defined by the inventive efforts made in each technological field k. Hence assignees change their positions on the map as a result of changes in their knowledge compositeness (an example is provided in Figure 5). In this way, the process captures ex-post changes in knowledge compositeness within and between technological fields. In order to retrieve this kind of information from the

[12] In order to remove the effect of the total number of firms that patented in each year, the measure is divided by the yearly number of firms that filed a patent in that year.

[13] For example, on a sample of US firms, Jaffe (1986) calculated the distribution of patents over 49 technological fields and measured the correlation (angular separation) between those vectors in order to detect the research efforts made in each innovative area, using the cosine index to obtain the similarity between firms' R&D activities. The cosine index provides the distance between two vectors. This procedure is then applied for all the pairs of observations within the dataset. By contrast, using SOM we calculate a distance between two nodes whose positions have been affected by all the other input data during the training stage.

technological space, we run a yearly SOM whose output is the input of the following neural network. The map thus records the entire information set within the input data, from the first to the last year of observation.
Several efforts have been made to include the dynamic perspective in the SOM algorithm (see Chappell and Taylor, 1993; Voegtlin, 2002; to cite a few). However, the methodology does not alter the original algorithm. In fact, using yearly input data makes it possible to detect the changes in the assignees' patent portfolios over time. Moreover, due to the fact that all the assignees (who carried out inventions in that year) are mapped together, the SOM output provides inter-assignees' similarities in those changes.

3.3 Environmental policy variables

The framework analyses the impact of the European policy portfolio on worldwide assignees' inventive activities. To this end, we focus on general economic and regulatory environmental policy instruments in Europe. In the following section we describe how our policy variables were built, and the data used to proxy them.

3.3.1 General economic instruments

Fuel price is one of the main drivers of environmentally-friendly technologies in the automotive industry (Aghion et al., 2012; Hascic et al., 2009). We employed IEA (International Energy Agency) data on post-tax gasoline prices[14] for households in the EU. Figure 6 shows the trend in the post-tax price of gasoline and diesel during the past twenty years. The level of the tax-inclusive price of gasoline rose until 2008 and fell during 2009, and then increased again from that year on. In addition, Figure 6 shows that total average fuel taxes followed a similar trend, though with a lower decrease in 2008-09.
Since our dependent variable (i.e. annual count of patents filed by each assignee) had assignee-level variation that we wanted to exploit, we weighted the tax-inclusive fuel price by the relative importance of country c for assignee i. Following Aghion et al. (2012) we assumed that the importance of each European country is related to the share of patents that the assignee has filed in those countries[15]. Therefore, the fuel price variable was defined as:

$$F\_PR_{i,t} = \sum w_{i,c} * F\_PR_{ct}$$

where F_PR_{ct} is the tax-inclusive fuel price for country c and $w_{i,c}$ is a time invariant weight related to the share of patent of assignee i in country c in the period 1990-1997[16].

Moreover, we investigated whether environmental vehicle taxes influence inventing activities. These kinds of taxes mainly charge vehicle purchases and ownerships in relation to the CO_2 vehicle emission rate (Klier and Linn, 2012). In particular, they can be levied one-off at the time of purchase or through a recurrent circulation tax (such as registration).
As part of the *ESA95 transmission programme*, Eurostat collects a *National Tax List* (NTL) from which environmental tax revenues are extrapolated[17]. Figure 6 also shows the trends in environmental transport taxes revenues from 1996 to 2012. The total amount of the revenue constantly increased until 2007, when it reached its highest level and then diminished until 2009.
In order to exploit assignee-level variation we weighted country-level environmental vehicle taxes by the importance of country c for assignee i. We followed the same procedure as before. Therefore:

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[14] Also diesel prices were tested. They provided similar results.
[15] The weighting procedure enabled us to account for the stringency level of policy measures, as well as their cross-country effects on assignees' patenting activities. However, Johnstone et al. (2010) have highlighted that also other design characteristics – such as predictability, flexibility, incidence and depth – affect the impact of environmental policy on patent production.
[16] In doing so, we tried to limit the endogeneity that might arise from the use of time variant weights: that is, the propensity to file patents in country c for assignee i may be higher if that country's fuel prices increase.
[17] These data are also available for environmental taxes levied on road transportation, which mainly includes vehicle ownership, vehicle use, other transport equipment, and related transport service taxations other than fuel taxes (Eurostat, 2001).

$$VEH\_T_{i,t} = \sum w_{i,c} * VEH\_T_{ct}$$

where VEH_T_{ct} is the amount of environmental vehicle taxes in country c at time t.

3.3.2 General regulatory instruments

In the European automotive industry, emission standards are introduced through directives and regulations as shown in Table 1. The right columns of Table 1 show that these standards impose limits on the release of air pollutants (such as CO, HC, NOx and PM), resulting in a gradual reduction of the pollutant emission thresholds over time.

In addition, the European Commission, introduced CO2 targets through voluntary commitment. Even if the agreement between the European Commission and automotive industry organisations was defined in 1998, the discussion on CO2 targets in the EU had started years before (Clerides and Zachariadis, 2008). In our time span (1999-2010), there was only one change of the upper limit of CO2 emissions, which was 140 g/km at the beginning of the time span and decreased to 130 g/km in 2008, the year of announcement of the last CO2 standard (Berggren and Magnusson, 2012).

Furthermore, as can be seen in Table 1 in the same period three emission standards were in force, i.e. Euro 3, Euro 4 and Euro 5.

Several empirical studies analyse European emission standards and CO2 targets through variables equal to 1 when the policy instruments come into force and 0 otherwise. The problem is that on using a dummy variable, some of the quantitative information retrievable from these standards (e.g. pollutant thresholds stringency, etc.) cannot be directly accounted for. In addition, emission standards dummy variables present a high degree of correlation (Hascic et al., 2009).

We ran the SOM in order to overcome the hurdles that derive from the dichotomous nature of using European emission standards and CO2 targets dummy variables.

After 1992, when Euro 1 was introduced, tighter pollutant limits were set by the regulator. In order to address this issue and to capture the stringency of general regulatory instruments, we ran a SOM in which each year from 1990 onwards was mapped relatively to the maximum pollutant thresholds allowed in that year.

Therefore, in the table below the structure of the input data presents, in each column, the pollutant limit imposed by the European emission standards and CO2 targets, whereas each row is the year to which they refer.

	CO	HC	HC+NOx	NOx	PM	CO2
1990	…	…	…	…	…	…
1991	…	…	…	…	…	…
…	…	…	…	…	…	…
2010	…	…	…	…	…	…

The distance in the SOM map between each input data (year) was calculated. From this map we obtained a continuous variable (STD_CO2) where the distance between these nodes was used as a proxy for the stringency of the generic regulatory instruments.

Furthermore, the maximum levels of allowed pollutants release decrease over time, as shown in Figure 7. We thus used the variable as a proxy for the upper limits of regulatory instruments.

Figure 7 clearly shows that the continuous variable captures the increasing stringency level of regulatory instruments over time. In order to test whether assignees anticipate the introduction of the policies by undertaking inventive activities before the effective implementation of such policies, we built the variable using the year of announcement of each European emission standard and CO2 target.

The variable was defined as follows:

$$STD\_CO2_{i,t} = \sum w_{i,EU} * STD\_CO2_{EU,t}$$

The methodology used to build the variable was the same as described above. However, in this case European emission standards and CO2 targets do not vary across European countries. Therefore, in order to account for the importance of the European market for each assignee, the weight $w_{i,EU}$ was calculated as the share of patents that assignee i filed in EU over the period 1990-97.

3.4 Other variables

The empirical model included additional variables in order to control for their effects on assignees' inventive activities. Firstly, we considered the impact of the geographical source of knowledge (i.e. firms close to knowledge producers increase innovative performances (Jaffe et al., 1993; Boschma, 2005)) in order to control for kinds of distance other than cognitive. For this purpose, we weighted the patents filed by other firms in other countries by the physical distance between their capital cities. Therefore, the more two firms were distant, the smaller the potential geographical spillover pool.

In addition, we controlled for assignee country patenting trends using the number of triadic patents filed in the assignee's country of origin. Using OECD data on triadic patent families, the aim of this variable was to control for wide patenting trends in the 'Emissions abatement and fuel efficiency in transportation'.

4 Empirical model

We used the following empirical model to test our hypotheses:

$$ln\ E\_PAT_{i,t} = \beta_1\ F\_PR_{i,t-1} + \beta_2\ VEH\_T_{i,t-1} + \beta_3 STD\_CO2_{i,t} + \beta_4\ PSP_{i,t-3} + \beta_5 KC_{i,t-1} + C_{i,t} + \alpha_i + Z_t + \varepsilon_{i,t}$$

where the dependent variable $EPAT$ is the annual count[18] of environmental patents filed by the assignee i at time t. F_PR is the amount of European-averaged post-tax fuel prices. VEH_T is the amount of environmental tax revenues (other than fuel taxes). STD_CO2 captures the trends in regulatory instruments (European emission standards and CO2 targets) stringency. As regards supply-side factors, KC refers to the knowledge compositeness of assignee i while PSP is the potential spillover pool. C is a set of variables that control for assignee varying factors such as the geographical stock of environmental knowledge and the patent activity trends in the assignee's country of origin. Finally, fixed effects α_i are introduced in order to retrieve unobservable assignee-specific heterogeneity, while Z_t accounts for time fixed-effects through which to control for global (macro) shocks that vary with time, i.e. external shocks that lead to market instability. $\varepsilon_{i,t}$, the error term, captures residual variation.

Due to over-dispersion of our dependent variable, as in several works that make use of count data as a dependent variable, we applied a fixed-effect negative binomial model (Cameron and Trivendi, 1998) to estimate the above equation on a sample of 355 assignees over 12 years (1999-2010).

All the variables had a one-year lag that allowed the assignee to respond to changes in environmental policy portfolios and supply-side factors. In addition, the PSP variable had a three-year lag in order to account for the time necessary to publish patent applications (usually 18 months for the EPO).

[18] In order to avoid the inclusion of occasional inventors, the model considers only those applicants that filed at least 3 patents between 1999-2010.

5 Results and discussion

We begin our discussion of the empirical model results by commenting on the significance of the coefficients obtained through the fixed effects negative binomial model (Table 4). Table 2 reports the descriptive statistics, while Table 3 shows the correlation matrix and the Variance Inflation Factors of each variable.

5.1 Environmental induced innovation hypothesis

5.1.1 General economic instrument

The results for the full sample of assignees, shown in Table 4 (column 1), highlight the positive and significant effect of general economic environmental policy instruments (i.e. F_PR and VEH_T). On the one hand, this confirms the findings of previous studies on the impact of fuel price on firms' innovative efforts (Hascic et al. 2009; Aghion et al. 2012). An upsurge in post-tax fuel prices stimulates applicants to increase their patenting activity in order to reduce the increasing cost of the factor's use, *de facto* confirming that, *ceteris paribus*, the environmental induced innovation hypothesis holds (*Hypothesis 1*). On the other hand, relatively unprecedented in the literature is the finding that environmental vehicle taxes, other than fuel taxes, positively influence the development of green inventions.

5.1.2 General regulatory instruments

An interesting result concerns the significance of the coefficients associated with the regulatory policy variable (i.e. STD_CO2), which highlights how assignees' environmental patenting activity is influenced by planned adoption and the increasing stringency of those regulatory instruments (*Hypothesis 2*). It therefore implies that a reduction in the maximum limit of pollutants that can be released (enhanced stringency), captured by our regulatory policy variable, increases the number of green patents produced. Thus, the findings suggest that assignees anticipate the introduction of emission standards and CO2 targets by developing inventions that allow compliance with policy requirements. This is due to the fact that the directives and regulations introducing the standards are published years before their legal (effective) implementation. According to Mickwitz et al. (2008), the introduction of new policy requirements, as well as increasing the stringency of existing ones, must be predictable and credible to boost environmental inventive performances. The time structure that we used seems to have been a valid means to include this kind of instrument in econometric models, from both the theoretical and methodological perspectives. Hence, the growing tightness of these policy instruments appears to have boosted environmental patenting activity in passenger cars, confirming H2.
Moreover, in order to gauge the effects of emission standards and CO2 targets separately, in Table 5 we run the model using dummy variables for each emission standard[19] and CO2 target weighted by the share of patents that the assignee filed in EU during the pre-sample period[20]. As will be seen, the variables Euro4, Euro5 and CO2 are statistically significant. On the one hand, the negative sign of CO2 targets provides insight into the effectiveness of this policy instrument because the reduction of the maximum level of CO2 allowed (and therefore the higher stringency of this policy instrument) stimulates green patenting activities. On the other hand, the negative signs of the Euro4 and Euro5 variables suggest that the variables have a lower effect on patenting activities with respect to Euro3[21]. This result may be explained by the fact that Euro3 introduced specific thresholds for hydrocarbons and mono-nitrogen oxides emissions for gasoline cars and mono-nitrogen oxides limits for diesel vehicles inducing a greater impact on green patenting with respect to the following regulations (Euro4 and Euro5).

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[19] The variables Euro4 Euro5 are equal to 1 from the year in which they are announced and 0 otherwise.
[20] We used the same weighting procedure as employed to build the STD_CO2 variable.

$$\mathrm{CO2}_{\mathrm{i,t}} = \sum \mathrm{w}_{\mathrm{i,EU}} * \mathrm{CO2}_{\mathrm{EU,t}}$$

where $\mathrm{w}_{\mathrm{i,EU}}$ is a time invariant weight that represents the share of patents of assignee I in EU, whereas $\mathrm{CO2}_{\mathrm{EU,t}}$ is the maximum limit of CO2 allowed in Europe at time t
[21] Euro3 is the omitted dummy variable.

5.1.3 Geographical impact of environmental policies

In order to test *Hypothesis 3*, we built different samples relative to the geographical location of the assignees[22]. Columns 2 and 3 (European and extra-European assignees respectively) of Table 4 highlight that, from a policy perspective, fuel prices and generic regulatory instruments impact on both European and non-European assignees, suggesting that these policy instruments are effective in inducing the development of environmental technologies also in other geographical areas. On the other hand, environmental vehicle taxes impact on inventive activities only for the European sample.

A possible explanation of these findings regards the level of risk experienced by domestic and foreign firms, which face environmental regulations in clearly different ways (Lee et al., 2011). The former are relatively closer to the home market, facilitating the search for long-term solutions (innovation) to comply with environmental policies. On the other hand, foreign firms need to balance challenges raised by policy requirements in both their home and foreign markets (Lee et al., 2011). However, other findings provided by Hascic et al. (2009) have highlighted that domestic regulations have a greater impact on foreign than domestic firms.

Moreover, also the relative stringency of policy instruments may influence the geographical impacts of environmental policy. Regulatory stringency distance between countries plays a pivotal role in the inducement of environmental inventions development (Dechezleprêtre et al., 2012). However, in the case of emission standards, a full comparison between these regulatory systems is not strictly feasible due to differences in their characteristics (e.g. test cycle processes, pollutants analysed, type of combustion and fuel) (Timilsina and Dulal, 2009; Vollebergh, 2010).

5.2 Innovation supply-side factors

Table 4 shows the positive and statistically significant effect of the potential spillover pool. These results confirm that more similar assignees (in term of efforts made in each technological field k) may extrapolate new information and ideas from the knowledge produced by others, and exploit them in other inventions. We do not know whether this knowledge is used by other inventors to generate new patents; but, as the results confirm, there is evidence that if the assignees are included in a technological space built through their research activity relatedness, the greater the knowledge produced by others and the smaller the cognitive distance between them, the higher the propensity to create new inventions. In contrast, assignees that make innovative efforts in technological fields that are distant (hence dissimilar), have a lower likelihood of being impacted by this flow of knowledge because they probably do not have the competencies necessary to absorb and retrieve the information included in patents filed by others. Hence, the output of our empirical model confirms *Hypothesis 4*.

As far as *Hypothesis 5* is concerned, dynamic knowledge compositeness also impacts positively on environmental patenting activities. This is due to two combined effects. On the one hand, increasing the quantity of inventions in a particular technological field enhances their absorptive capacity in that technological area and therefore the ability to identify useful research paths to be undertaken. On the other hand, knowledge compositeness at the applicant level measures the variety of complementarity in the various technological fields. Our results confirm that an increase in the capacity to handle heterogeneous competencies leads to the pursuit of successful inventive activities in several fields.

[22] The country of the assignees was obtained from the assignee's address field in the patents.

6 Conclusions

The study has considered the literature on policy-induced effects and knowledge production factors that influence the rate and direction in which knowledge is produced. The main hypotheses tested shed light on the positive impact of environmental policies and intrinsic characteristics of knowledge on environmental knowledge production.

It has been found that European environmental policies, considered as a whole, affect the worldwide production of environmental patents. Specifically, tax-inclusive fuel prices, environmental vehicle taxes and generic regulatory instruments, i.e. European emission standards and CO2 targets, are the main drivers of this effect.

It is thus possible to outline some policy implications. Fuel price is one of the main drivers of technological efforts on green automotive technologies. In addition, this policy instrument impacts on both European and non-European assignees. However, policy makers should pay attention to the relative and absolute stringency of their instruments. Indeed, domestic policy instruments may be less strict than in other foreign countries avoiding the development of new technologies to comply with domestic environmental regulation, and allowing the diffusion of inventions developed to comply with other regulations. Finally, as far as regulatory instruments (European emission standards and CO2 targets) are concerned, the development of green inventions seems to be induced when they are announced. On the one hand, this may enable policy makers to partially assess the effectiveness of their interventions before the effective implementation of general regulatory instruments. On the other hand, this result emphasises the effectiveness of predictable and credible policy interventions.

Furthermore, on trying fully to endogenize technological change, the study has analysed the influence of internal and external knowledge characteristics, such as the potential spillover pool and dynamic knowledge compositeness, on the development of environmental patents. It has found that the variety of technological fields exploited by applicants favours their capacity to take technological opportunities that enhance the production of environmental patents.

Finally, the results emphasise that, in a globalised industry like the automotive one, cognitive proximity between knowledge produced is one of the main features to be considered when studying what triggers environmental patent production. That is, the more closely two assignees are placed in the technology space, the greater their possibility to exploit knowledge externalities from knowledge produced by other applicants (that compose the potential spillover pool). However, further research is required to investigate what technological knowledge is more likely to be exploited by others and the potential interaction between this issue and institutional factors.

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Appendix A

List of CPC subclasses and their description:
(Y02 - Technologies or applications for mitigation or adaptation against climate change)
(Y02T - Climate change mitigation technologies related to transportation)

Y02T 10/00 - Road transport of goods or passengers

Y02T10/10 - Internal combustion engine [ICE] based vehicles

Y02T10/12 - Technologies for the improvement of indicated efficiency of a conventional ICE

Y02T10/14 - Technologies for the improvement of mechanical efficiency of a conventional ICE

Y02T10/16 - Energy recuperation from low temperature heat sources of the ICE to produce additional power

Y02T10/17 - Non-reciprocating piston engines, e.g. rotating motors

Y02T10/18 - Varying inlet or exhaust valve operating characteristics

Y02T10/20 - Exhaust after-treatment

Y02T10/30 - Use of alternative fuels

Y02T10/40 - Engine management systems

Y02T10/50 - Intelligent control systems e.g. conjoint control

Y02T10/60 - Other road transportation technologies with climate change mitigation effect (not used, see subgroups)

Y02T10/62 - Hybrid vehicles

Y02T10/64 - Electric machine technologies for applications in electromobilty

Y02T10/70 - Energy storage for electromobility (hydrogen internal combustion engines Y02T90/42 ; fuel cell powered electric vehicles Y02T90/34)

Y02T10/72 - Electric energy management in electromobility

Y02T10/76 - Transmission of mechanical power

Y02T10/80 - Technologies aiming to reduce green-house gasses emissions common to all road transportation technologies

Y02T10/82 - Tools or systems for aerodynamic design

Y02T10/84 - Data processing systems or methods, management, administration

Y02T10/86 - Optimisation of rolling resistance.

Y02T10/88 - Optimized components or subsystems e.g. lighting, actively controlled glasses

Y02T10/90 - Energy harvesting concepts as power supply for auxiliaries' energy consumption e.g. photovoltaic sun-roof

Y02T10/92 - Energy efficient charging or discharging systems for batteries, ultracapacitors, supercapacitors or double-layer capacitors specially adapted for vehicles

Y02T90/42 - Hydrogen as fuel for road transportation

Y02T90/32 - Fuel cells specially adapted to transport applications, e.g. automobile, bus, ship

Y02T90/34 - Fuel cell powered electric vehicles [FCEV]

Y02T90/14 - Plug-in electric vehicles

Y02T90/16 - Information or communication technologies improving the operation of electric vehicles

Appendix B

The process by which the SOM maps the input data begins with the initialisation phase where an empty map is generated and a vector is assigned (randomly or linearly) to each neuron (Kohonen, 2013).
The SOM is a lattice of nodes (called map) where each neuron (node) is connected to its neighbours. For each node, a weight vector (Wv) is assigned during the initialization phase. This vector, of course, must have the same length as the input vectors. Subsequently, in the next step of the SOM's algorithm, the initialised map is trained with the multidimensional input data. Using a distance measure (typically the Euclidean distance), the algorithm assigns each piece of input data to the most similar neuron. The node that minimises the vector distance between the weight of the node and the input data itself is labelled Best-Matching Unit (BMU).
Subsequently, the neighbouring nodes around the BMU are modified to make them more similar to the winning neuron. The process is iterated N times, and in each iteration the radius that determines the size of the BMU neighbourhood shrinks, until only the best-matching neuron is included in it.
That is, the map starts to train itself by selecting the input vectors from the database and traversing each node in the map. The Euclidean distance (ED) between the weight vector of each node (Wv) and the selected input vector is calculated. During the following steps the map begins to learn from the dataset how to represent it, first by modifying the BMU weight vector and then by updating the weight vectors of the BMU neighbours as well (trying to pull them closer to the BMU). The neurons weight vector is updated through the following learning formula:

(1) $\mathrm{Wv}(t+1) = \mathrm{Wv}(t) + \theta(v,t)\alpha(t)(\mathrm{D}(t) - \mathrm{Wv}(t))$

where $\mathrm{Wv}(t+1)$ is the node weight at time $t+1$, while $\mathrm{Wv}(t)$ is the node weight assigned in the previous step. $\mathrm{D}(t)$ is the input vector and, as explained above, $\mathrm{D}(t) - \mathrm{Wv}(t)$ is the Euclidean distance between input and node vectors. Finally, $\alpha(t)$ is a monotonically decreasing learning coefficient and $\theta(v,t)$ is the Gaussian neighbourhood function, where v is a single neuron.

The SOM's algorithm is useful for understanding how this NN works:
(a) Initialise the map's nodes' weight vectors (initialisation phase).
(b) Select an input vector from the dataset.
(c) Traverse each node in the map using the Euclidean distance formula to find similarity between the input vector and the map's nodes weight vector.
(d) Track the node with the smallest distance as the best matching unit (BMU).
(e) Update the nodes in the neighbourhood of BMU by pulling them closer to the input vector through formula (1).
(f) Increment t and repeat from (b) while $t < \lambda$.

The SOM's algorithm stops after λ number of cycles, where in each cycle the process is repeated for each input vector.
Recently, the use of a Batch algorithm (BA) has been proposed as an alternative to the sequential algorithm (Kohonen, 2013). It has been acknowledged that the BA produces more accurate results employing less computational efforts. The difference between the two algorithms resides in the way input data are presented to the SOM (Step b and c). In the BA all the input data are presented to the map at the same time (epoch). Subsequently the nodes' weights are modified in order to capture the similarity between them, reducing the influence on the final map of the order in which input data are presented to the map.
Hence, the process first defines the BMU for each input vector without modifying the map nodes. When the whole set of input is associated to a node, the weight of each neuron is updated. This is carried out through the calculation of the mean of the input data assigned (in the previous step) to the neurons placed in the kernel defined by the neighbourhood function.

Appendix C

The following table presents the main keywords associated with each cluster. In order to retrieve this information, we applied the Term Frequency / Inverse Document Frequency to calculate the importance of the words included in the title and abstract of each patent.

Cluster	Main keywords	# of patents
1	Rubber, diene, tire	3953
2	Battery, recharge, connector	1632
3	Cooler, turbocharger, supercharger	2324
4	NOx, particulate, purification	1307
5	Clutch, gear, transmission	446
6	Ammonia, Selective catalytic reduction	3011
7	Washcoat, zeolite, cerium	388
8	Shaft, gear, planetary	858
9	Honeycomb, porous, ceramic	923
10	Cell, anode, cathode	829
11	Camshaft, stroke, valve	586
12	Restart, stop, clutch	435
13	Electrolysis, hydrogen, tetravalence	173
14	Injector, stroke	1952
15	Hybrid, traction, battery	713
16	Lithium, electrolyte, battery	1439
17	Exhaust gas recirculation, injector	2193
18	Battery, package, cell	1408
19	Torque, hybrid, powertrain	1768
20	Intake, piston, swirl	2024
21	Cerium, alumina, zirconium	538
	Total	28900

Figures

Figure 1 - Overview of the theoretical framework

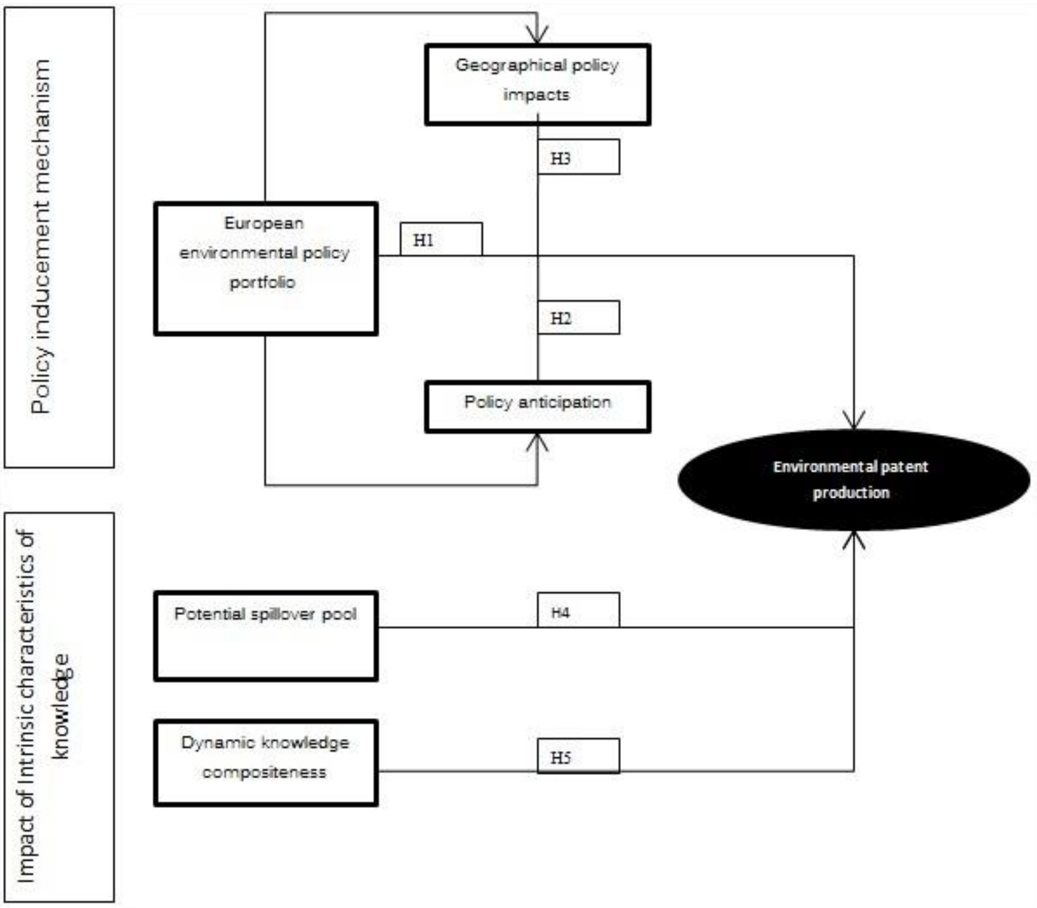
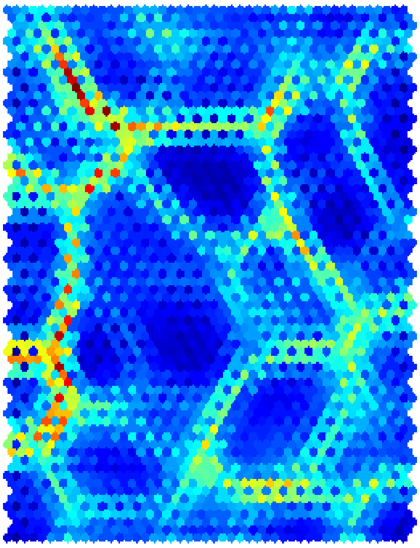
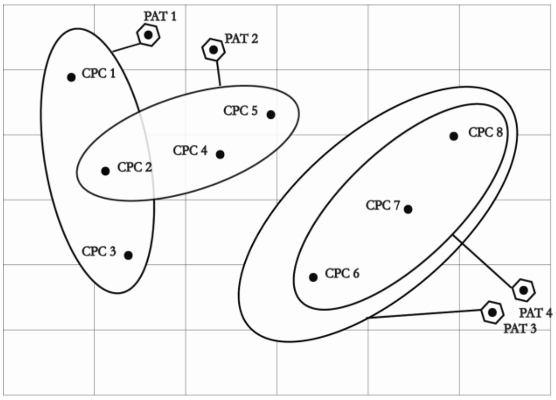


Figure 2 - SOM represented as a Unified-distance Matrix using patent classes assigned to each patent as input data



The colour indicate the distance between a node and its closest neighbour node.

Figure 3 – Example of a patent map created using the SOM



As an example, this figure shows that Patent 1 and Patent 2 share one CPC class, i.e. CPC 2. At the bottom, Patent 3 and Patent 4 have the same set of CPC codes. Therefore, due to their technological similarities, Pat 3 and 4 are placed in the same position, i.e. distant from Pat 1 and 2 (which refer to different technical developments). Finally, Pat 1 and 2 are located close to each other but not in the same position (due to the fact that they share just one CPC class).

Figure 4 – Clustering results of the SOM map using k-mean algorithm (each colour corresponds to a cluster of nodes)

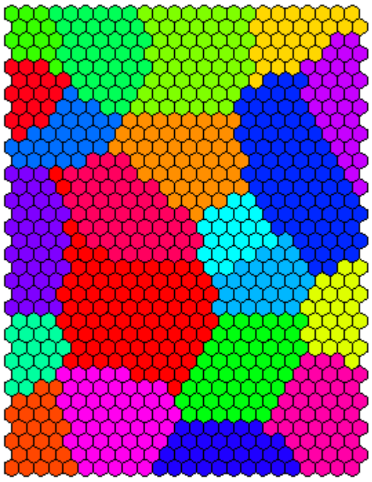
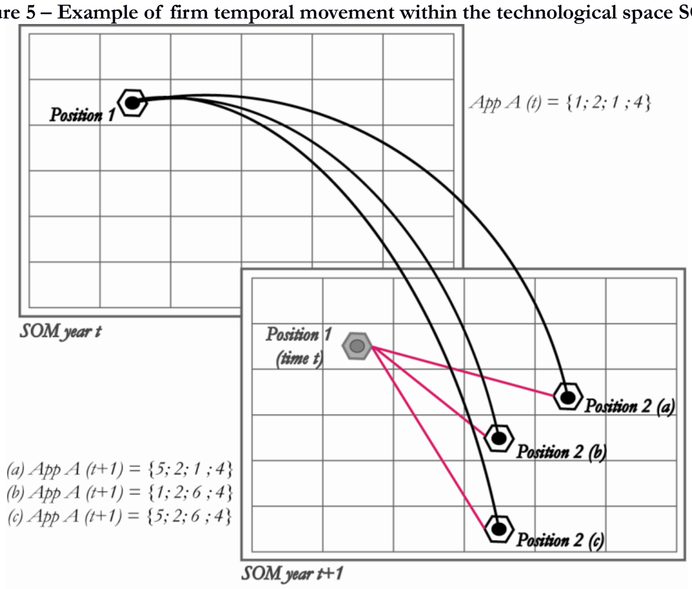
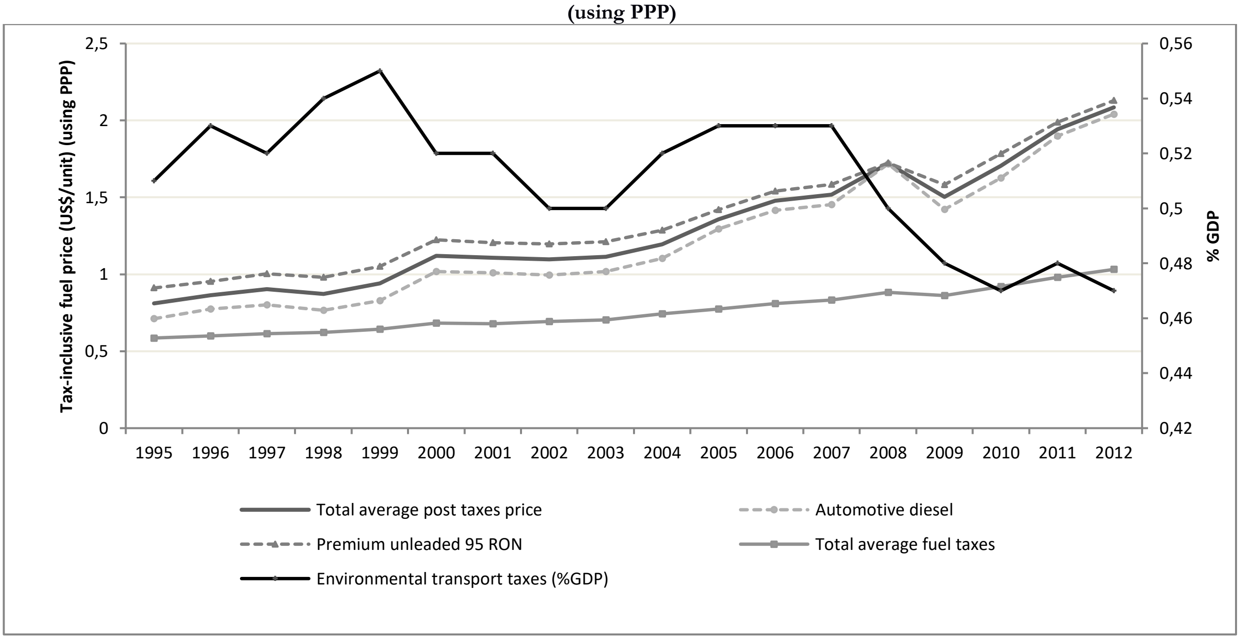


Figure 5 – Example of firm temporal movement within the technological space SOMs



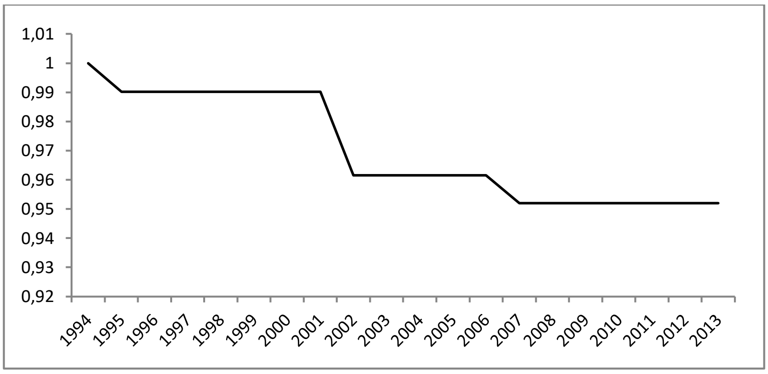
The figure shows that the movements of Applicant A from position 1 (in year t) to position 2 (in year t+1) can derive from (a) changes in the number of patents within the technological field k, (b) changes in the technological field k3 (different from k1) and (c) a combination of both.

Figure 6 – Transportation environmental taxes, gasoline and diesel EU average post-tax prices and relative taxes from 1995 to2012 (US$/unit) (using PPP)



Source: Own figure using data from IEA and Eurostat (2013)

Figure 7 – Trend in generic economic instrument upper limit threshold. (1994 = 1)



Source: Own figure using data from Section 3.3.2.

Tables

Table 1 – Directives, Regulations and pollutant thresholds* of European emission standards

Label (year)	Directives and Regulations	CO	HC[a]	HC+NOx	NOx	PM
Euro 1 (1992)[b]	Directives 91/441/EEC (passenger cars only) or 93/59/EEC (passenger cars and light trucks)	2,72		0,97		0,14
Euro 2 (1996)	Directives 94/12/EC or 96/69/EC	1,6		0,7		0,1
Euro 3 (2000)	Directive 98/69/EC, further amendments in 2002/80/EC	1.47	0.1	0.56	0.325	0.05
Euro 4 (2005)	Directive 98/69/EC, further amendments in 2002/80/EC	0.75	0.1	0.3	0.165	0.03
Euro 5 (2009)	Regulation 715/2007	0.75	0.1	0. 23	0.12	0.01

**Average between compression ignition and positive ignition vehicles*
[a] *Total hydrocarbon*
[b] *also known as EC 93*

Source: Directive 98/69/EC, 2002/80/EC, Regulation 715/2007

Table 2 – Descriptive statistics

	Obs.	Mean	SD	Min	Max
E_PAT	*4260*	*3.438967*	*15.43946*	*0*	*341*
ln F_PR	*4260*	*.2371509*	*.1893159*	*-.2071779*	*.7503148*
ln VEH_T	*4260*	*-.7486518*	*.2158486*	*-1.379324*	*.2700271*
ln STD_CO2	*4260*	*-.7051191*	*.6108135*	*-4.254884*	*-.0585877*
PSP	*4260*	*.2148628*	*.3792365*	*0*	*10.75574*
KC	*4260*	*1.126179*	*2.582743*	*0*	*52.03686*
GSEK	*4260*	*.2111096*	*.1419714*	*0*	*.4371135*
CUM_PAT	*4260*	*204.2037*	*198.5615*	*0*	*619*

Table 3 – Correlation matrix and VIF

	VIF	*1/VIF*	*ln F_PR*	*ln VEH_T*	*ln STD_CO2*	*PSP*	*KC*	*GSEK*	CUM_PAT
ln F_PR	*1.22*	*0.816*	*1.0000*						
ln VEH_T	*1.07*	*0.932*	*-0.0846*	*1.0000*					
ln STD_CO2	*1.24*	*0.803*	*-0.0844*	*-0.0844*	*1.0000*				
PSP	*1.00*	*0.995*	*0.0031*	*0.0128*	*-0.0433*	*1.0000*			
KC	*1.02*	*0.984*	*0.0422*	*-0.0687*	*-0.0104*	*0.0452*	*1.0000*		
GSEK	*2.71*	*0.368*	*0.0231*	*-0.1973*	*-0.2169*	*0.0154*	*0.0927*	*1.0000*	
CUM_PAT	*3.14*	*0.318*	*-0.2215*	*-0.0865*	*-0.3638*	*0.0100*	*0.0759*	*0.7572*	*1.0000*
Mean VIF	*1.63*								

Table 4 – Regression coefficients for fixed-effects negative binomial model (full, EU and extra-EU samples)

	Full sample	*EU*	*Extra-EU*
	(1)	(2)	(3)
ln F_PR (t-1)	*3.9704**** *(0.9446)*	*2.8694*** *(1.2693)*	*5.5781**** *(1.5613)*
ln VEH_T (t-1)	*0.8043**** *(0.2801)*	*1.0099**** *(0.3643)*	*0.5455* *(0.4801)*
ln STD_CO2	*-0.5566**** *(0.1082)*	*-1.3897**** *(0.3181)*	*-0.3452*** *(0.1447)*
PSP (t-3)	*0.1696**** *(0.0360)*	*0.1368**** *(0.0412)*	*0.2541**** *(0.0961)*
KC (t-1)	*0.0585**** *(0.0042)*	*0.0540**** *(0.0057)*	*0.0772**** *(0.0079)*
Controls			
GSEK (t-3)	*0.5579* *(0.4156)*	*0.0554* *(0.7891)*	*1.5364*** *(0.7006)*
CUM_PAT (t-1)	*0.0000* *(0.0002)*	*-0.0001* *(0.0007)*	*-0.0004* *(0.0004)*
Year Dummies	*YES*	*YES*	*YES*
N	*4260*	*2076*	*2184*
Chi2	*326.70*	*164.63*	*192.42*
AIC	*9825*	*4658*	*5157*
BIC	9946	4765	5265

Model results for the full sample, European assignees (EU) and Extra-European assignees (Extra-EU) subsamples. Dependent variable: count of green patents. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 – Regression coefficients for fixed-effects negative binomial model using dummy variables

	Full sample (1)
ln F_PR (t-1)	3.9704***
	(0.9446)
ln VEH_T (t-1)	0.8044***
	(0.2801)
Euro4	-1.4808***
	(0.4088)
Euro5	-1.7016***
	(0.5165)
ln CO2	-0.5566***
	(0.1082)
PSP (t-3)	0.1696***
	(0.0360)
KC (t-1)	0.0585***
	(0.0042)
Controls	
GSEK (t-3)	0.5581
	(0.4156)
CUM_PAT (t-1)	0.0000
	(0.0002)
Year Dummies	YES
N	4260
Chi2	327
AIC	9825
BIC	9946

Model results for the full sample. Omitted dummy variable Euro3. Dependent variable: count of green patents. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$