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by

Nicolò Barbieri

31/2014

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SEEDS Working Paper 31/2014
December 2014
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Investigating the impacts of technological position and European environmental regulation on green automotive patent activity

Nicolò Barbieri*

Abstract

Using patent data on 355 applicants patenting to the European patent offices from 1998 to 2010 on environmental road transport technologies, we investigate under what conditions the European environmental transport policy portfolio and the intrinsic characteristics of assignees' knowledge boost worldwide green patent production. Our findings suggest that post-tax fuel prices, environmental vehicle taxes, CO2 standards and European emission standards, introduced in 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, we advocate that assignees anticipate the introduction of those emission standards, filing patents before the effective implementation of regulations when legislations are announced.

Furthermore, we provide evidence that in a technological space (which measures the applicants' technological proximity), closely located organisations 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 taking advantage of the knowledge produced by others. Finally, we observe that dynamic changes (both in quantity and in the number of technological fields engaged) in assignees' patent portfolios spur inventive performances.

Keywords: Environmental patents, environmental policies, Self-Organising Maps, road transport technologies, European emission standards, fuel prices.

JEL: O31, O38, Q55, L62

* Department of Economics - University of Bologna, Strada Maggiore, 45 - 40125 Bologna, Italy; Ingenio CSIC-UPV, Valencia, Spain. E-mail: n.barbieri@unibo.it

1 Introduction

In a complex framework such as long-term climate policy analysis, market failures play a pivotal role, 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 made by policy makers, which create the incentives to internalize and share the costs of pollution, would encourage firms to pollute too much and innovate too little with respect to the social optimum (Johnstone et al. 2010a).

Even if the related literature on the environmental policy-induced innovation has provided evidence that green policy spurs eco-innovation (see Popp et al. (2009) 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 from 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 bridge the gap in understanding endogenous technological change[2]. Thus, the study of this dynamic interaction appears relevant since investments in technological knowledge are exposed to uncertainty, high costs, information asymmetry and positive externalities (i.e. other firms may benefit without incurring in all the development costs) (Jaffe et al., 2005), all of which may reduce innovative performances, even though environmental policies were properly designed.

Using patents as a proxy for invention, the present paper delves into what triggers green invention development, enclosing both the European environmental policy portfolio and the intrinsic characteristics of knowledge, that impact on the rate and direction of technological change, in the analysis, i.e. the potential stock of environmental knowledge and dynamic knowledge compositeness. The former stands upon the notion of cognitive distance (Boschma, 2005) and we investigate whether this distance between internal and external knowledge favours the creation of environmental technologies. The latter is defined as internal knowledge variety across technological fields (Antonelli and Calderini, 2008) and we analyse if its dynamics impact technological change.

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

The innovative contributions that this paper provides are manifold. Firstly, it introduces the so-called Self-Organising Map (SOM) (Kohonen, 1982, 1991, 2001) into innovation

[2] Popp (2002) and Aghion et al. (2012) are a few exceptions.

and environmental economics literature, an unsupervised Neural Network (NN) technique able to detect similarities in multidimensional data and represent them in a two-dimensional map where a global order is achieved. The added value of this methodology is that it allows us to create distance-based maps where the patents, assignees or emission standards are mapped in relation to their specific and relative characteristics. Most importantly, the similarity between the mapped items can be measured and used in empirical analysis.

Secondly, through the exploitation of this methodological tool, for the first time we unpack the box of environmental inventions, discerning between several sub-fields of inventive activities that compose the total environmental stock of patents related to passenger cars. In opposition to existent literature on the automotive industry that generally analyses two broad technology groups (e.g. integrated technologies vs. post-combustion technologies (Hascic et al., 2009) or internal combustion engine vs. electric and hybrid innovation (Aghion et al., 2012), we consider a more detailed technological framework that enables us to build supply-side variables in an innovative way, based on assignees' positions in a technological space (Jaffe, 1986).

Thirdly, we investigate whether firms are able to anticipate the effective introduction of mandatory environmental policies by developing inventions when regulations are announced.

Finally, from a theoretical perspective, 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 application within a patent family, whose priority country is European), whether the geographical context impacts assignees' response to regulatory changes.

The paper is structured as follows: Section 2 presents the related literature on both the environmental induced innovation and the knowledge characteristics that spur innovative performances. In Section 3 we describe the methodological framework through which the independent variables are built. Section 4 introduces the empirical model, Section 5 describes the results, and finally, Section 6 concludes.

2 Theoretical background and provable hypotheses

2.1 Environmental policies and innovation

During last decades several scholars investigated the relationship between environmental policies and technological change, the results of which provide evidence on a positive relationship between them (Green et al., 1994; Porter and Van der Linde, 1995; Kemp, 1997; Rennings, 2000).

Popp et al. (2009) have 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) have 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. On the contrary, Brunnermeier and Cohen (2003) have obtained a positive relationship between green patents and PACE.

In a recent comparative study between the automotive and energy sector, Bergek et al. (2014) has explored how types of environmental policy instruments affect innovation. Their findings have highlighted that different policy instruments trigger different types of innovation. 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) instruments. On the other hand, they diverge on the basis of their technological neutrality, i.e. specific or general instruments. 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) have triggered modular innovation. Finally, technology-specific instruments are suitable to spur the development of radically new technologies.

In this direction, different studies have analysed the effect of various policy instruments on green automotive technologies. The main reasons reside in the availability of information related to firms' innovative capabilities, the high environmental impact and the consequent broad range of policies that regulate this sector. Indeed, in order to face the challenge posed by growing environmental impact associated with vehicle GHGs release, environmental regulation plays a pivotal role in incentivising firms to enhance car fuel efficiency (Clerides and Zachariadis, 2008). That is, in a static picture, environmental policies alter the trade-off between the marginal cost of introducing such regulations and their social marginal benefit (Jaffe et al., 2005).

Economic instruments provide the incentives to adopt and develop low-emitting technologies, in the form of economic compensation for the avoided social cost of pollution (Bergek et al., 2014). The literature related to general economic instruments has mainly examined the effect of fuel taxes on boosting the development of low-emitting technologies. Aghion et al. (2012) have analysed the effect of tax-inclusive fuel prices on patent activities across worldwide firms. The results provide insights of 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 explored what spurs innovation beyond fuel prices. This class of polices (e.g. registration taxes, purchase taxes and subsidies, etc.) had been scrutinised by Klier and Linn (2012), who discussed the role of such instruments in promoting cars registrations and average vehicle CO2 emission rates. While they found that these taxes had a significant negative effect on new vehicle registration, their analysis provided little evidence on the decrease in long-run vehicle emission rates.

However, the majority of the studies investigated the effects of environmental policy portfolios that embraces both general economic and regulatory instruments. This approach brings to a more comprehensive policy framework enabling comparison between different types of environmental policies.

Regulatory instruments mainly include technology, emission or performance standards. In this case, the objective of the regulator is controlling the actions of firms directly prescribing a certain behaviour. In the automotive sector the main general regulatory policy instruments are fuel economy standards, CO2 standards and noxious emission standards. As far as the former is concerned, Clerides and Zachariadis (2008) have found that the introduction or adoption of more stringent fuel economy standards and fuel prices has improved new-car fuel efficiency. In addition, they have 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 affected automotive green patent activities in the others. The results from their study showed that green inventions were impacted in a greater and positive way by foreign regulation than domestic standards.

Lee et al. (2011), underlined the positive effect that US technology-forcing auto emission standards had 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.

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

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

Expected policy changes: Most environmental problems are characterised by uncertainty surrounding future environmental impacts and, consequently, how future policies respond to them (Jaffe et al., 2005). In addition, the uncertainty related to policy maker commitment to increase environmental regulation stringency may result counterproductive for firms' investments in R&D activities (Bansal and Gangopadhyay 2005; Mickwitz et al., 2008), incentivising firms to behave strategically inducing the regulator to reduce or postpone tight standards (Lutz et al., 2000; Puller, 2006). This issues alters future R&D returns, and thus the way in which firms react to environmental policy changes depends on expected future resource prices (Jaffe et al. 2002).

Recently, several authors focused on policy design features rather than policy type (Johnstone et al., 2010b). This branch of literature emphasizes that environmental policies should be classified through a vector of policy characteristics such as stringency, predictability, flexibility, incidence and depth.

Even if such features are difficult to measure (Johnstone et al., 2010b) the present paper discusses the effects of policy stringency (introduced above) and predictability and their effect on firms environmental patenting activity.

Economic uncertainty can threat investment decisions (Pindyck, 2007). This is particularly true when those investments regard R&D activities the outcome of which is unpredictable ex-ante (Nelson and Winter, 1982). In addition, environmental policy uncertainty may exacerbate this issue. Indeed, uncertain signals and irreversible investments may result in investment postponing (Johnstone et al., 2010b)

Whereas environmental policy stringency has been analysed in several papers, the effect of predictability remains substantially unchartered at least from an empirical perspective. Söderholm et al. (2007) ascribe the slow rate of development in wind power technologies across Denmark, Germany and Sweden to policy instability due to the sequence of different subsides that are present for short period of time.

Lee et al. (2010) has 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, subjects may anticipate the introduction of the policy instrument due to lower uncertainty. Berggren and Magnusson (2012) have highlighted that car makers anticipated CO2 restriction reducing emissions when the EU legislation had been announced (2008) instead of waiting for its implementation (2012-15).

Hascic et al. (2009) pointed out that foreign regulations had a greater impact on domestic firms than domestic regulations. This can be explained by the capability of home firms to anticipate 'the introduction of the regulation that is not as much of a policy shock' (Hascic et al., 2009, pp. 13).

Our objective is assessing whether general regulatory policies such as CO2 targets and European emission standards affect environmental patenting activities before their effective implementations. Hence:

Hypothesis 2. Assignees anticipate the introduction and the tightening of emission standards pursuing inventions before their implementations, at the time of their announcements.

Geographical policy impacts: Different 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 literature has focused on the third stage of the technological change (Schumpeter, 1942) in which inventions, after their inclusion in products and processes (innovation), start to be diffused. The majority of these studies has provided clear evidence that absolute environmental policy stringency induces the transfer of green technologies. Only recently, Dechezleprêtre et al. (2012) underlined the role played by relative regulation stringency on the transfer of environmentally sound technologies between recipient and source countries.

These works paid attention to the innovative efforts pursued in a specific country and subsequently transferred to foreign countries. Just few studies (e.g. Hascic et al., 2009) analysed the relationship between domestic environmental regulations and foreign production of eco-innovation. The use of dummy variables to specify whether emission standards were in force did not permit them to test if a tightening in the pollutant thresholds induced innovation in other geographical areas. The focus, in this paper, is no longer the transfer of technologies produced abroad, but innovation produced in foreign countries to comply specifically with foreign regulations, e.g. the Japanese firm that developed an invention specifically to comply with US emission standards, rather than divulging already disclosed inventions (maybe developed to comply with stricter national regulations) in that market. Therefore, another hypothesis that our work tests is:

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

2.2 Supply-side factors and innovation

As well as environmental policies that impact positively on innovation imposing a cost on pollution, knowledge externalities that arise from the creation of new knowledge may hamper this effect. The public-good nature of new knowledge brings innovating firms to capture only a fraction of the whole benefit generated by 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 that supply-side factors have 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. His results showed that the existing base of scientific knowledge, together with energy prices, triggered energy-efficiency innovation. In addition, the author 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 hampered 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 stimulated 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.

Our paper adds some elements to this literature through the exploration of how cognitive distance impacts on environmental inventions. Given the fact that people sharing the same knowledge may learn from each other (Boschma, 2005), the knowledge stock produced by other firms may influence knowledge production if their cognitive base is close enough to communicate, understand and process it successfully (Boschma and Lambooy, 1999). Indeed, effective transfer of knowledge needs absorptive capacity to take place, i.e. the capabilities to recognise, decode and exploit the new knowledge (Cohen and Levinthal, 1990).

To this regard, through the creation of a technology space that captured the similarity between firms patent stocks, Jaffe (1986) found that R&D productivity had been enhanced by the R&D output of those firms that had a closer technological position within the technology space. Therefore:

Hypothesis 4. Assignees with lower cognitive distance between their environmental technological fields have a higher likelihood of increasing their own patent activity.

What is more, 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 the inventors, influences the rate at which inventions are effectively introduced in the industry (Antonelli and Calderini, 2008). In addition, firms' innovative performances and their technological diversification are subjected to technological opportunities that characterise the industry (Nieto and Quevedo, 2005). In principle, technological opportunities, defined as the potential for technological advances both in general as well as in specific innovative fields (Olsson, 2005), crucially influence variation within innovation portfolios (at firm and industry levels) and the quantity of innovation pursued.

Although, the related literature does not provide a complete answer to whether firms that change their technological portfolio by broadening the type and increasing the quantity of inventions, enhance their capabilities to detect and exploit new knowledge that would bring to an upsurge in their patent production. Hence:

Hypothesis 5. Changes in applicants' knowledge compositeness result in a spur of environmental inventive output.

3 Patent data and variables

In order to retrieve information on firms' inventing performances such as (i) technological field, (ii) technical description, (iii) country in which innovation is carried out and (iv) when it was developed, the paper makes use of patent data. Patents are a good indicator of innovative efforts due to the fact that they are usually filed in the earlier steps of the innovative process (Griliches, 1990). In addition, 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, patents cannot be considered as an indicator of innovation but rather of inventions, due to the fact that they have not yet reached market introduction (Leydesdorff et al., 2014). Therefore, we use patent data as a proxy for inventions. Nevertheless, we must be aware that (i) not all inventions are patented, (ii) there are differences in the commercial value of patents (some invention may have little commercial value) and (iii) sometimes they have a weak correlation with R&D expenditure (Popp, 2005). Even with the presence of such limitations, the exploitation of patent data is widespread in our related 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 stock of assignees that pursued inventive activities on environmental road transport technologies, we used 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]. We retrieved 30,348 patents filed to European patent offices (including the European Patent Office (EPO)) from 1990 to 2012.

[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, that are used as a proxy for the scope of the invention.

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

Moreover, many scholars have tracked the patterns of technology diffusion using patents filed to different countries as a proxy for technology diffusion. These 'duplications' of the original patent return inventors’ willingness to market invention in those countries (Popp, 2005), e.g. if a patent is firstly filed in Japan and a few years later in Germany, it means that the assignee considers Germany as a second potential market for its invention.

The diffusion process is impacted by factors that are different from those that affect invention. Therefore, the present work avoided the inclusion of duplicated patents. Firstly because our focus is on inventive processes rather than on the analysis of what drives inventions’ diffusion. Secondly, 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 may distort our results.

In order to track the inventive efforts pursued to comply with European policy framework, we collected the whole patent family[5] of each invention. These are 236,960 documents that include: 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 in any of the European patent offices[6] we included it in our dataset. The final result was a dataset that, after considering co-patenting[7] and removing observations with missing values (some of the patents had no assignee name, application country, etc.), accounted for 28,917 patents, with a total of 4,942 assignees from EU and non-EU countries.

3.1 Using SOM to unpack the “box” of environmental inventions

From a technological point of view, firms involved in competitive markets try to reach the best position in a technological space relative to their competitors, developing a portfolio of inventions that allows them to achieve this result. This position is characterised by a vector $F = (F_1 \dots F_k)$ 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 firms in this space allows us to measure the cognitive distance between firms that carried out more similar inventive activities; i.e. firms are located closer if their research activities are similar and far away otherwise.

To define the k technological fields, we used an unsupervised neural network (NN) technique, named Self-Organising Map (SOM) (Kohonen, 1988; 1990; 2001). The SOM is a two-layer competitive NN that represents multidimensional data onto a two-dimensional topological grid (Kohonen, 2001). This technique is a nonlinearity projecting mapping in which the input data becomes spatially and globally ordered relatively to the similarity that the process finds within input data (Kohonen, 2012). It is able to reduce a complex nonlinear statistical relationship into a more simple, easy to understand and graphically attractive low-dimensional display (Kohonen et al. 1996) in which it

[5] Patent families are collections of all the patents that refer to the same invention.
[6] 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
[7] Some patents are developed by more than one assignee together. We consider the co-patented invention as a single patent for each assignee.

preserves the topological relationship between input data that tends to be clustered. The theoretical backbone of the SOM resides on a lattice of interconnected nodes (neurons) to which input data is assigned through the similarity pattern that the process retrieves in the sample.

The SOM is a lattice of nodes (called map) where each neuron is connected to its neighbours. For each node, a weight vector (Wv) is assigned during the initialization phase[8]. This vector, of course, must have the same length as the input vectors. Subsequently, in the next step of the SOM' algorithm (detailed in Appendix B), 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, each 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 interaction the radius that determines the size of the BMU neighbourhood shrinks, until just the best-matching neuron is included in it.

We created a patent map (PM) through SOM using co-classification of 4-digit IPC classes assigned to each patent. Almost all the patent documents published worldwide make use of the International Patent Classification system (IPC), established by the Strasburg Agreement in 1971, which labels patents according to their technological content through a hierarchical, language-independent classification system. The assumption is that the presence of the same IPC 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 strength 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 4-digit IPC classes assigned to each patent, while in the rows the patent ID:

	IPC 1	IPC 2	…	IPC m
Patent 1	…	…	…	…
Patent 2	…	…	…	…
…	…	…	…	…
Patent n	…	…	…	…

The advantage of applying the SOM with this kind of input data is that it enables us to detect technological similarities between patents calculating their distance in the patent map (PM). PMs allow for a visual representation of the patent analysis result, and their strength resides on the facility to obtain information from and about the mapped items.

The output of the SOM (Figure 1) is a PM where the patents that provide similar (different) technological improvements are placed closer (distant) (exemplified in Figure 2). Finally, using a k-means algorithm (MacQueen, 1967), we detected 20 technological clusters, to which each patent had been assigned through the SOM (Figure 3).

[8] The assignment can be random (random initialisation) or, as in our case, through a 'regular, two-dimensional sequence of vectors taken along a hyperplane spanned by the two largest principal components' of the input data (linear initialisation) (Kohonen, 2012 pp.6).

3.2 Supply-side variables

Once the k technological areas are identified, we run the SOM to obtain the similarities across assignees' innovative efforts. In this application, the neural network locates the firms in the technological space, a two-dimensional grid of neurons (nodes), where each assignee is placed in relation to its patent distribution over technological fields. Thus, within this technological space, assignees with similar research activities are mapped close compared to those that carry out very different innovative efforts (placed far away).

The input data for this application was the number of patents filed in each k technological field in column and, as observation unit, the assignees:

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

Two firms with identical patent portfolios are located in the same neuron, otherwise, perfectly orthogonal vectors far away. Thus, measuring the distance between two firms, and therefore between two neurons on the map, we obtain a new measure of distance that we use as a proxy for the cognitive distance between them.

We measure the potential stock of environmental knowledge ($PSEK$) for firm i at time t as follows:

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

Where $EPAT_{j,t}$ are environmental patents filed by another firm j at time t. $DIST_{i\,j}$ is the nodes distance on the map between the two firms. Finally, s is the total number of firms. In this way, the stock of external knowledge available for firm i increases when the patent count of firm j increases, and decreases when the distance increases. In order to remove the effect of the total number of firms that patented in each year, we divide our measure by the yearly number of firms that filed a patent in that year.

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 resides in the capability to reach a local and global order within the map. It does not provide a similarity measure between pairs of objects, but between the whole of observations in the dataset[9].

[9] 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 to detect the research efforts performed 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. Subsequently, this procedure is protracted for all the pairs of observations within the dataset. On the contrary, using SOM, we

In addition, the SOM is useful in defining the dynamic patterns that characterise firms' positions in the technological 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 pursued in each technological field k. Thus, we point out that assignees change their positions on the map as a result of changes in their knowledge compositeness (an example is provided in Figure 4). 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 technological space, we run a yearly SOM whose output is the input of the following neural network. Doing this, the map records the entire information set within the input data, from the first to the last year of observation.

Several efforts were pursued to include the dynamic perspective into the SOM algorithm (Chappell and Taylor, 1993; Voegtlin, 2002; to cite a few). However, our methodology does not alter the original algorithm. In fact, using yearly input data allows us 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

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

3.3.1 General economic instruments

Fuel taxes and post-tax fuel prices are some of the main drivers of environmentally-friendly technologies in the automotive industry. Even though fuel taxes are considered a common instrument to increase government revenues, they reduce the externalities generated by the transport sector (i.e., pollutant emissions and traffic congestion) (Timilsina and Dulal, 2011). Basically, this reduction is achieved through a decrease in yearly vehicle mileage (Eltony, 1993) and a drop in fuel consumption. On the other hand, fuel taxes generate incentives for innovative activities in emission-control technologies (Hascic et al. 2009) that cause an abatement in pollutants release.

We use IEA (International Energy Agency) data on post-tax gasoline prices[10] for households in the EU. Figure 5 shows the trend in the post-tax price of gasoline and diesel during the last twenty years. The level of the tax-inclusive price for gasoline and diesel fuels rose until 2008 and fell during 2009, starting to increase again from that year

calculate a distance between two points whose positions have been affected by all the other similar data input during the training stage.

[10] Diesel prices and average price between diesel and gasoline prices have been tested. They provide similar results.

on. In addition, we can observe from Figure 5 that total average fuel taxes follow a similar trend, though with a lower decrease during the 2008-09 years.

Since our dependent variable (i.e. annual count of patents filed by each assignee) has assignee-level variation that we want to exploit, we weight tax-inclusive fuel price by the relative importance of country c for assignee i. Following Aghion et al. (2012) we assume that the importance of each European country is related to the share of patents that the assignee has filed in those countries. Therefore, the fuel price variable is 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[11].

Moreover, we investigate 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[12]. It should be noted that in this case we use environmental transport tax revenues as a proxy for the level of general environmental regulation related to the transport sector. Figure 5 also shows the trends in environmental transport taxes revenues from 1995 to 2012. The total amount of the revenue constantly increased until 2007, when it reached its highest amount and started to diminish until 2009.

In order to exploit assignee-level variation we weight country level environmental vehicle taxes by the importance of country c for assignee i. We follow the same procedure as before; therefore:

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

3.3.2 General regulatory instruments

The EU automotive industry has cut nitrogen oxide (NOx) and particulate matter (PM) releases by about 90% during the last 25 years. This improvement was also achieved through the compliance strategies that automotive firms applied in order to meet the European emission standards that challenged the whole industry.

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[11] In doing so, we tried to limit endogeneity that might arise from the use of time variant weights. That is, the propensity to file patents in country c for assignee i, might be higher if fuel prices of that country increase.

[12] This data is also available for environmental taxes levied on road transportation, that mainly includes vehicle ownership, vehicle use, other transport equipment and related transport service taxations, other than fuel taxes (Eurostat, 2001).

In the European automotive industry, emission standards are introduced through directives and regulations as shown in Table 1. We observe from the right columns of Table 1, that these standards imposed limits to air pollutant release (such as CO, HC, NOx and PM), resulting in a gradual reduction of the pollutant emission thresholds over time (Figure 6).

In several empirical studies, European emission standards are introduced through variables equal to 1 when the policy instruments come into force and 0 otherwise. The problem is that using a dummy variable, some of the quantitative information retrievable from the emission standards (e.g. pollutant thresholds stringency, etc.) is not directly considered, causing a loss of information. In addition, emission standards dummy variables present an high degree of correlation (Hascic et al., 2009).

In this work we run the SOM in order to overcome the hurdles that derive from the dichotomous nature of using European emission standards dummy variables.

Since 1992, when Euro 1 was introduced (Figure 6), tighter pollutant limits were set by the regulator. In order to address this issue and to capture emission standards stringency, we run a SOM where the European emission standards (Euro 1, 2, 3, 4, 5) are mapped relative to their pollutant thresholds. In each column, the structure of the data input presents the pollutant limit imposed by the directive and, in each row, the European emission standard to which it refers. Therefore each emission standard is defined as a vector of pollutant limits. That is:

	Pollutant 1	Pollutant 2	…	Pollutant m
Euro 1	…	…	…	…
Euro 2	…	…	…	…
…	…	…	…	…
Euro n	…	…	…	…

Figure 7 shows a unified-distance matrix (UMAT) where we detect the nodes in which the European emission standards are located. The distance between each adjacent node is represented in the vertical axis.

We observe that Euro 1 is placed far away from Euro 4 and 5 because the difference in pollution limits between these regulations is high. Conversely, Euro 4 and Euro 5 present similar emission limits and therefore they are located in closed positions.

From this map we obtained a continuous variable (STD) where the distance between these nodes is used as a proxy for the stringency of the European emission standards. Using node distances, we miss the first observation related to Euro 1 (1992). However, this does not impact the reliability of our study that focuses on the years between 1997-2010. In addition, as specified in Bergek et al. (2014), whereas initial stringency is characterised by uncertainty in the policy setting search process, successive stringency increases are important to avoid innovation fade out.

Furthermore, the maximum levels of allowed pollutants release decrease over time. Thus, we use this variable as a proxy for emission standards upper limits (Figure 8).

Figure 8 clearly shows that our continuous variable captures the higher stringency of European emission standards. In order to test whether assignees anticipate the introduction of the policies pursuing inventive activities before their effective implementations, we build the variable using the year of announcement of each European emission standards.

The variable is defined as follow:

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

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

Finally, we analyse CO2 target introduced through voluntary commitment by the European Commission. This policy instrument imposes new passengers cars a reduction of 25% of CO2 released per kilometre, compared to 1995 values (Berggren and Magnusson, 2012). Even if the agreement between European Commission and automotive industry organisations had been defined in 1998, the discussion started years before (Clerides and Zachariadis, 2008). Therefore, in our time span (1997-2010) we just record one change of the upper limit of CO2 emissions that starts at 140 g/km at the beginning of the time span and decreases to 130 g/km in 2008, year of the announcement of the last CO2 standard (Berggren and Magnusson, 2012). In order to capture how this variable impact green patent activities and to avoid correlation with other policy variables described above, we weight the CO2 target by new vehicle registrations in the European countries. In doing so, we account for the importance of country markets defined as the share of total new vehicle registrations in that country. We assume that the less the share of new vehicles registered in country c, the less the impact of the CO2 target in that country. Due to the fact that this variable captures country level variation while our dependent variable has assignee level variation, we weight this variable using pre-sample share of patent in each European country by assignee i (as described above). Therefore, our variable is defined as:

$$CO2_{i,t} = \sum w_{i,c} * (\gamma_{c,t} * CO2\_T_{EU,t})$$

Where $\gamma_{c,t}$ is the share of new vehicle registrations in country c (EUROSTAT, 2013) and $CO2\_T_{EU,t}$ is the European upper limit to CO2 emissions.

3.4 Other variables

The empirical model includes additional variables in order to control for their effects on assignees' inventive activities. Firstly, we consider the impact of 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 other kinds of distances than the cognitive one. In doing so, we weight the patents filed by other firms in other countries by the physical distance between their capital cities. Therefore, the more two firms are distant, the less the geographical stock of environmental knowledge available.

In addition, we control 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 is 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:

$$\begin{aligned} ln\, E\_PAT_{i,t} = {} & \beta_1\, F\_PR_{i,t-1} + \beta_2\, VEH\_T_{i,t-1} + \beta_3 STD_{i,t} + \beta_4\, CO2_{i,t} + \beta_5\, PSEK_{i,t-3} \\ & + \beta_6 KC_{i,t-1} + C_{i,t} + \alpha_i + Z_t + \varepsilon_{i,t} \end{aligned}$$

Where the dependent variable $EPAT$ is the annual count[13] 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) as a percentage of GDP. STD captures the trends in European emission standards stringency. $CO2$ represents the CO2 targets in EU. As far as supply-side factors are concerned, KC refers to the knowledge compositeness of the assignee i while $PSEK$ is the potential stock of environmental knowledge produced by other assignees j that can be exploited by the assignee i. 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 country of origin. Finally, fixed effects α_i have been introduced in order to retrieve unobservable assignee-specific heterogeneity, while Z_t accounts for time fixed-effects through which we 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 to estimate the equation above (Cameron and Trivendi, 1998).

All the variables present a one-year lag that allows the assignee to response to changes in environmental policy portfolios and supply-side factors. In addition, the $PSEK$ variable has a 3 year lag in order to account for the time necessary to publish patent applications (usually 18 months for the EPO).

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.

[13] In order to avoid the inclusion of occasional inventors, the model considers only those applicants that filed at least 3 patents between 1990-2013.

5.1 Environmental induced innovation hypothesis

The results related to the full sample of assignees, shown in Table 4 (column 1), highlight the fact that general economic environmental policy instruments (i.e. F_PR and VEH_T) are positive and significant. On the one hand, this confirms 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 use of the factor becoming more expensive, *de facto* confirming that, *ceteris paribus*, the environmental induced innovation hypothesis holds. On the other, relatively new to the literature we observe that environmental vehicle taxes, other than fuel taxes, positively influence technological development in low-emission vehicles.

An interesting result arises from the significance of the coefficients associated to regulatory environmental instruments (i.e. $CO2$ and STD), that highlight how assignees' environmental patenting activity is influenced by planned adoption and increasing stringency of those regulatory instruments (*Hypothesis 2*). Notice that in this case higher stringency implies a reduction of maximum limit of pollutants release, captured by our regulatory policy variables, that are associated with smaller values of E_PAT. Thus, our findings suggest that assignees anticipate the introduction of emission standards, developing inventions that allow to comply with policy requirements. This is due to the fact that the directives and regulations through which the standards are introduced, are published years before their legal implementation. According to Mickwitz et al. (2008) the introduction of new policy requirements, as well as increasing the stringency of existing ones, have to be predictable and credible to boost environmental inventive performances. The time structure that we used seems to represent a valid choice to include this kind of instrument in econometric models, both from 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, our results provide evidence that economic policy instruments lead to a greater impact on environmental patenting activity than regulatory policies. This result backs conventional wisdom where market-based instruments are more suitable to induce innovation than CAC regulations (Vollebergh, 2007; Requate, 2005).

In order to test *Hypothesis 3*, we built different samples relative to the geographical location of the assignees[14]. Columns 2 and 3 (European and extra-European assignees respectively) of Table 4 highlight that, from a policy perspective, fuel prices and European emission standards impact both European and non-European assignees. On the other hand, environmental vehicle taxes and CO2 standards impact inventive activities only throughout the European sample.

These findings are explained by two main issues. Firstly, as far as post-tax fuel prices are concerned, their positive impact is hardly surprising since they are one of the main instruments to spur green invention within the transport policy framework. In addition, the difference in the values of these coefficients (column 4) confirms that domestic regulations have a greater impact on foreign than domestic firms (Hascic et al., 2009). That is, if we compare the level of fuel prices across the three main markets (i.e. Europe,

[14] The country of the assignees has been obtained from the assignee's address field in the patents.

North America and Japan) we can notice that fuel prices have always been higher in Europe than in the other two geographical areas (Figure 9). Indeed, comparing the F_PR coefficients between the three sub-samples (Table 5) we can observe that lower fuel prices (compared to European ones) are associated to greater impact of this policy variable. In this case, absolute stringency and regulatory stringency distance (relative stringency) play a pivotal role in the inducement of environmental inventions production (Dechezleprêtre et al., 2012).

The same framework should be useful to compare emission standards across countries, since European emission standards are stricter than Japanese ones (at least as far as CO emissions are concerned). However, 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).

A possible explanation to that brings our discussion to a second issue that emerges from model results. The level of risk experienced by domestic and foreign firms facing environmental regulation is clearly different (Lee et al., 2011). As explained above, 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 side, the foreign firms need to balance challenges coming from policy requirements in both their home and foreign markets (Lee et al., 2011). Therefore, as we can observe from Table 4, the whole set of European policy variables impact European assignees, while only a portion of them influence patenting activities in both sub-samples.

5.2 Innovation supply-side factors

Table 4 shows the positive and statistically significant effect of the potential stock of environmental knowledge. These results confirm that when assignees disclose their inventions to the public audience, more similar assignees (in term of efforts pursued in each technological field k) may extrapolate new information and ideas from that knowledge that may be exploited within other inventions. We do not know whether this knowledge is practically used from other inventors to generate new patents but, as the results confirm, we find 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 lesser the cognitive distance between them, the higher the propensity to create new inventions. In contrast, assignees that carry out innovative efforts in technological fields that are distant (hence dissimilar), have a smaller likelihood to be impacted by this flow of knowledge due to the fact that they probably do not have the required competencies 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, knowledge compositeness at the applicant level measures the variety of complementarity in the different technological fields. Our results confirm that an increase in the capability to handle heterogeneous competencies leads to the pursuit of successful inventive activities in several fields.

6 Conclusions

Based on a panel of 355 assignees patenting to the European patent offices from 1998 to 2010 on environmental road transport technologies, the present work accounted for the interaction between market failures associated to environmental damage and knowledge production. In order to fully understand what spurs patent production related to environmental technologies, the paper tries to endogenize technological change to provide an unbiased environmental policy analysis.

The study encompassed 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.

We found that European environmental policies, considered as a whole, affect the worldwide production of environmental patents. Specifically, tax-inclusive fuel prices, environmental vehicle taxes, European emission standards and CO2 standards are the main drivers of this effect.

In doing so, we were able to provide some policy implications that enhance the understanding of policy maker intervention consequences. The induced effects of environmental policies vary across the regional areas in which organisations are located. Our findings suggest that relative distance in regulation stringency assumes a pivotal role in transport-related inventions boosted by tax-inclusive fuel prices. On the other hand, it seems reasonable to think at the influence of domestic and foreign regulations on inventive activities. That is, whereas domestic assignees are likely to find long-term solutions to comply with domestic regulations, foreign assignees should match the requirements imposed by their domestic and foreign environmental policies that regulate home and foreign markets. This may explain why the environmental policies considered in our paper have a greater impact on European (home) assignees than on foreign ones.

In addition, our findings confirmed that both European and extra-European assignees anticipate the effective implementation of general regulatory policy instruments by actively increasing their inventive performances when legislations are announced.

Furthermore, trying to fully endogenize technological change, we analysed the influence of internal and external knowledge characteristics, such as the potential stock of environmental knowledge and dynamic knowledge compositeness, on the development of environmental patents. We found that the variety of technological fields exploited by applicants favours their capability to undertake technological opportunities that enhance the production of environmental patents.

Finally, the results emphasize that in a globalised industry such as the automotive one, cognitive proximity between knowledge produced is one of the main features to be considered in the study of what triggers environmental patent production. That is, the more two assignees are closely placed in the technological space, the greater their possibility to undertake knowledge externalities from knowledge produced by other applicants. 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

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 through 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, 2012).
After the initialisation step, 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. The neuron with the lowest ED is labelled as Best Matching Unit (BMU). During the following steps the map begins to learn from the dataset how to represent it, firstly modifying the BMU weight vector and secondly 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) $\mathrm{Wv}(\mathrm{t}+1) = \mathrm{Wv}(\mathrm{t}) + \theta(\mathrm{v},\mathrm{t})\alpha(\mathrm{t})(\mathrm{D}(\mathrm{t}) - \mathrm{Wv}(\mathrm{t}))$

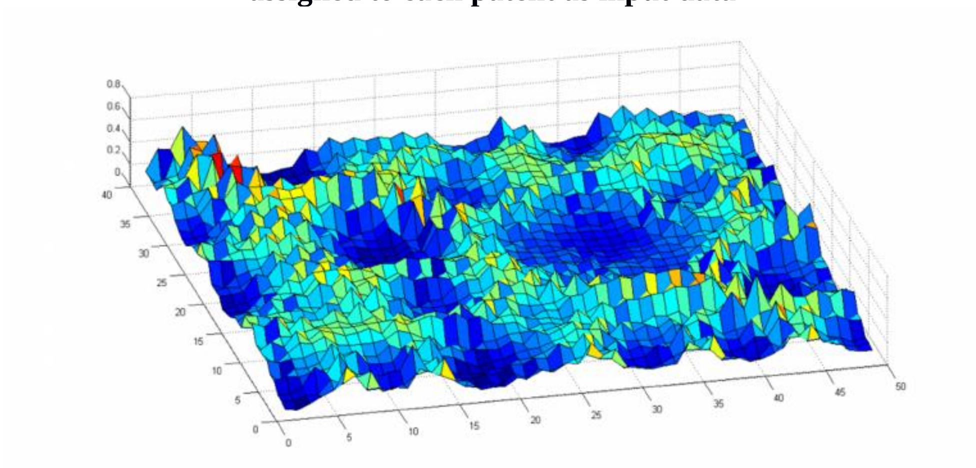
Where $\mathrm{Wv}(\mathrm{t}+1)$ is the node weight at time $\mathrm{t}+1$, while $\mathrm{Wv}(\mathrm{t})$ is the node weight assigned in the step before. $\mathrm{D}(\mathrm{t})$ is the input vector (patent count of each firm in each technological field – single row of the previous table) and, as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

The SOM's algorithm is useful to understand how this NN works:
(a) Randomise the map's nodes' weight vectors (initialisation phase).
(b) Select an input vector from the dataset (single row of the table).
(c) Traverse each node in the map using 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 $\mathrm{t} < \lambda$.

The SOM's algorithm stops after λ number of cycles, where in each cycle the process is repeated for each input vector.

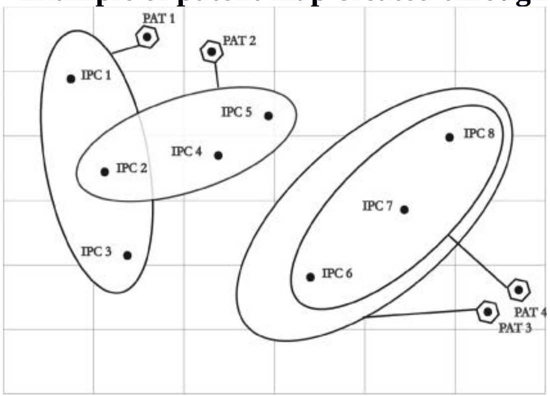
Figures and Tables

Figure 1 - SOM represented as a Unified-distance Matrix using patent classes assigned to each patent as input data



The vertical axes as well as the color return the distance between a node and its closest neighbor.

Figure 2 – Example of patent map created through the SOM



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

Figure 3 – Clustering results of the SOM map using k-mean algorithm (each color corresponds to a cluster of nodes)

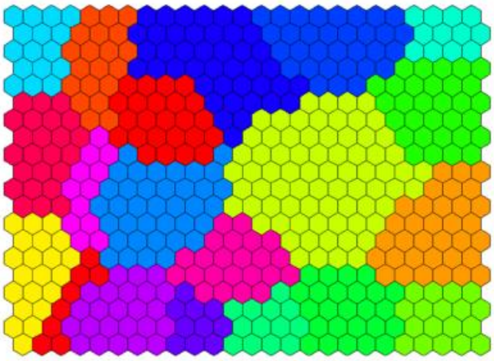
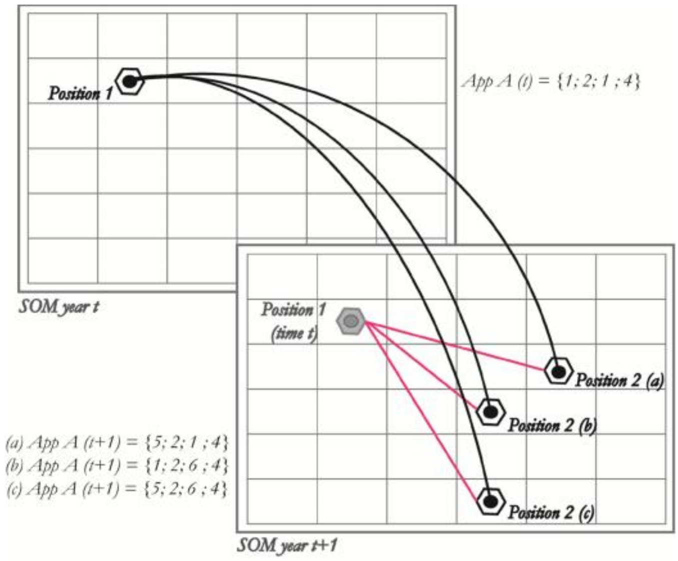
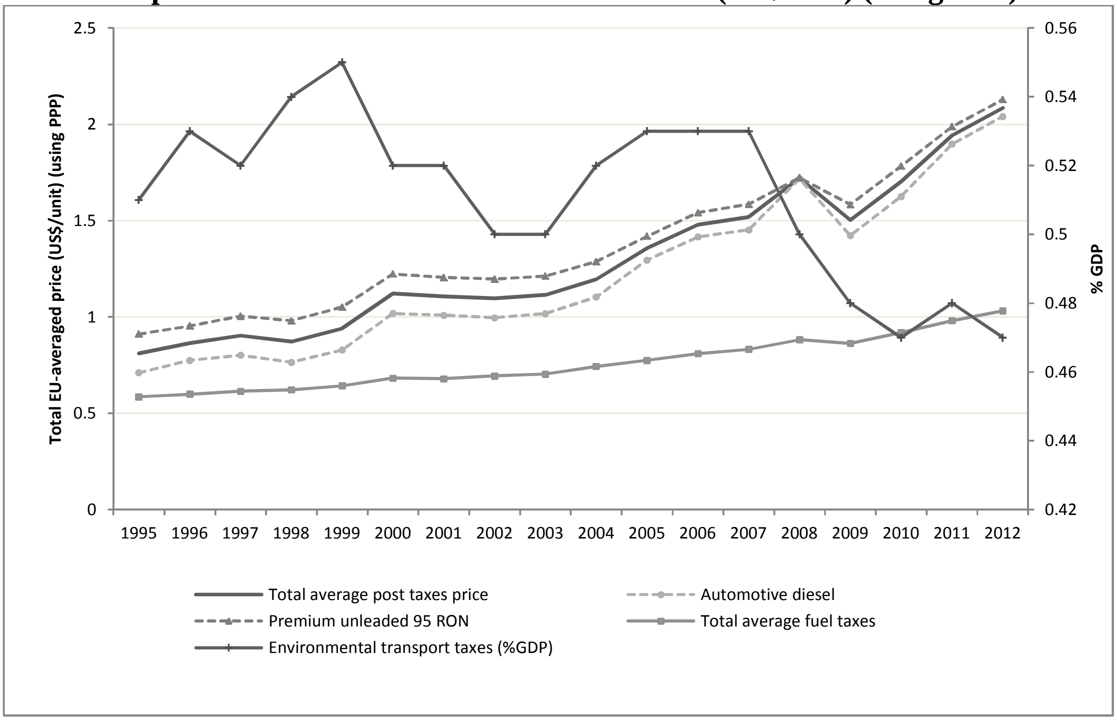


Figure 4 – Example of firm temporal movement within the technological space SOMs



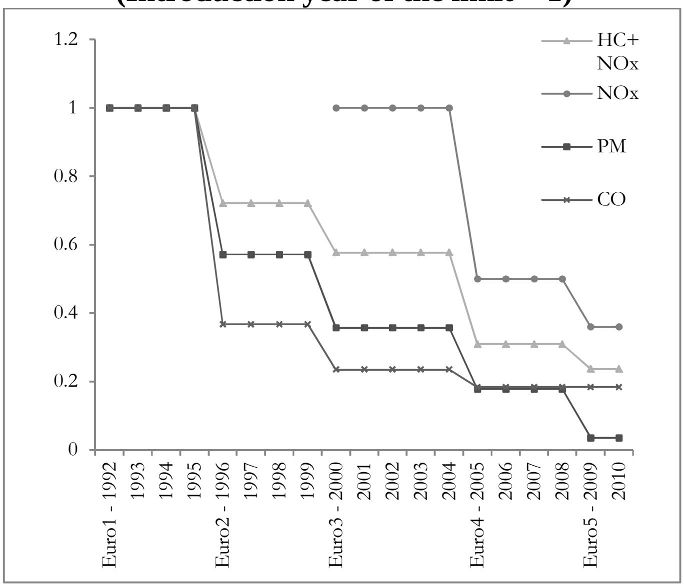
The figure shows that the movements of the Applicant A from position 1 (in year t) to position 2 (in year t+1) can derive from (a) changes in the number of patents within the technological field k, (b) changes in the technological field k3 (different from k1) and (c) a combination of both.

Figure 5 – Transportation environmental taxes, gasoline and diesel EU average post-tax prices and relative taxes from 1995 – 2012 (US$/unit) (using PPP)



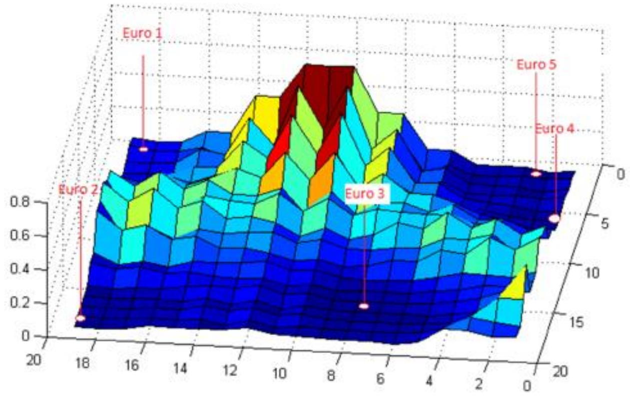
Source: Own figure using data from IEA and Eurostat (2013)

Figure 6 – Trends in in emission standards stringency for compression ignition vehicles of the regulated pollutants. (Introduction year of the limit = 1)



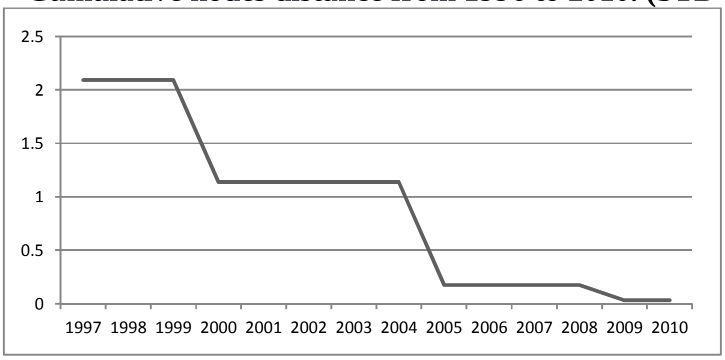
Source: Own figure using data from respective EU directives in Table 2

Figure 7 – SOM represented as a Unified-distance Matrix with HC+NOx, NOx, PM, CO emission limits as input data (hot colours are associated with a greater distance between adjacent nodes – which is reported in the vertical axis)



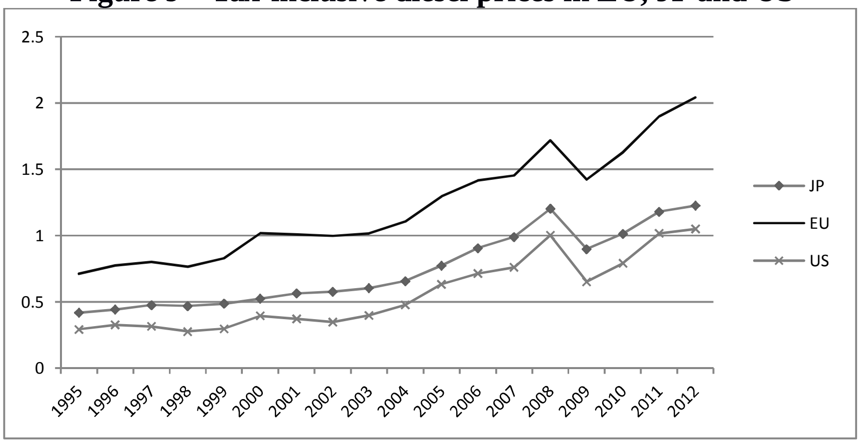
Source: Own figure using data from respective EU directives in Table 2

Figure 8 – Cumulative nodes distance from 1996 to 2010. (STD variable)



Source: Own figure using data from SOM

Figure 9 – Tax-inclusive diesel prices in EU, JP and US



Source: Own figure using data from IEA (2013)

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

	Mean	SD	Min	Max
E_PAT	*3.054438*	*14.29076*	*0*	*341*
ln F_PR	*.2149534*	*.1976201*	*-.2071779*	*.7503148*
ln VEH_T	*-.7485887*	*.2161459*	*-1.620611*	*.2700271*
ln CO2	*4.151854*	*.5002885*	*-.1968498*	*4.941642*
ln STD	*-2.297095*	*1.533815*	*-7.589935*	*.1286735*
PSEK	*.3374846*	*.5263037*	*0*	*11.24337*
KC	*.9827679*	*2.126231*	*0*	*29.77715*
GSEK	*.2057051*	*.1430034*	*0*	*.4371135*
CUM_PAT	*199.8733*	*192.8133*	*0*	*619*

Table 3 – Correlation matrix and VIF

	VIF	*1/VIF*	*ln F_PR*	*ln VEH_T*	*ln CO2*	*ln STD*	*PSEK*	*KC*	*GSEK*	CUM_PAT
ln F_PR	3.94	.253	1							
ln VEH_T	1.06	.941	-0.0887	1						
ln CO2	1.05	.952	0.0294	0.0366	1					
ln STD	3.55	.281	-0.8338	0.0303	-0.0689	1				
PSEK	1.02	.982	0.0029	-0.0006	0.0191	-0.0161	1			
KC	1.03	.967	0.0420	-0.0647	0.0249	-0.0298	0.1235	1		
GSEK	2.70	.369	0.0234	-0.1824	0.1655	-0.0936	0.0329	0.1114	1	
CUM_PAT	2.93	.341	-0.2221	-0.0760	0.1936	0.0555	0.0159	0.0942	0.7600	1
Mean VIF	2.16									

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)	*4.1045**** *(0.9723)*	*2.5298** *(1.3051)*	*5.8484**** *(1.5744)*	*χ 2 = 12.56**** *Prob > χ2 = 0.000*
ln VEH_T (t-1)	*0.8896**** *(0.2958)*	*1.1297**** *(0.3913)*	*0.4826* *(0.4882)*	*χ 2 = 3.04** *Prob > χ2 = 0.081*
ln CO2	*-0.3019**** *(0.1170)*	*-0.3122** *(0.1651)*	*-0.2535* *(0.1763)*	*χ 2 = 0.00* *Prob > χ2 = 0.976*
ln STD	*-0.4082**** *(0.1039)*	*-1.2154**** *(0.3197)*	*-0.2692** *(0.1432)*	*χ 2 = 8.53**** *Prob > χ2 = 0.003*
PSEK (t-3)	*0.2311**** *(0.0448)*	*0.3942**** *(0.0678)*	*0.1036** *(0.0622)*	*χ 2 = 7.19**** *Prob > χ2 = 0.007*
KC (t-1)	*0.0764**** *(0.0059)*	*0.0864**** *(0.0083)*	*0.0642**** *(0.0087)*	*χ 2 = 2.66* *Prob > χ2 = 0.103*
Controls				
GSEK (t-3)	*0.7761** *(0.4140)*	*0.5919* *(0.7832)*	*1.8479**** *(0.7091)*	
CUM_PAT (t-1)	*0.0000* *(0.0002)*	*-0.0003* *(0.0007)*	*-0.0003* *(0.0004)*	
Year Dummies	*YES*	*YES*	*YES*	
N	*4226*	*2057*	*2169*	
Chi2	*334*	*213*	*154*	
AIC	*9720.7172*	*4574.7703*	*5138.9323*	
BIC	9848	4687	5253	

Model results for the full sample, European assignees (EU) and Extra-European assignees (Extra-EU) subsamples. In columns 4 we test the null hypothesis that two coefficients are equal. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 - Regression coefficients of Fixed-effects negative binomial for EU, Asian, North America subsamples.

	EU	*NA*	*H0: β Eu – β NA=0*	*AS*	*H0: β Eu – β AS=0*
	(1)	(2)	(3)	(4)	(5)
ln F_PR (t-1)	2.5298*	4.8093*	*χ 2 = 0.22*	3.8553*	*χ 2 = 23.35****
	(1.3051)	(2.6175)	*Prob > χ2 = 0.640*	(2.1478)	*Prob > χ2 = 0.000*
ln VEH_T (t-1)	1.1297***	1.1520	*χ 2 = 0.01*	0.3814	*χ 2 = 6.57***
	(0.3913)	(0.7596)	*Prob > χ2 = 0.907*	(0.7348)	*Prob > χ2 = 0.0104*
ln CO2	-0.3122*	0.3173	*χ 2 = 1.21*	-0.3461	*χ 2 = 0.26*
	(0.1651)	(0.3400)	*Prob > χ2 = 0.271*	(0.2215)	*Prob > χ2 = 0.609*
ln STD	-1.2154***	0.2557	*χ 2 = 0.05*	-0.5334***	*χ 2 = 16.77****
	(0.3197)	(0.2797)	*Prob > χ2 = 0.828*	(0.1756)	*Prob > χ2 = 0.000*
PSEK (t-3)	0.3942***	0.0520	*χ 2 = 6.00***	0.1214	*χ 2 = 4.75***
	(0.0678)	(0.1020)	*Prob > χ2 = 0.014*	(0.0821)	*Prob > χ2 = 0.029*
KC (t-1)	0.0864***	0.1257***	*χ 2 = 2.62*	0.0421***	*χ 2 = 6.33***
	(0.0083)	(0.0193)	*Prob > χ2 = 0.105*	(0.0109)	*Prob > χ2 = 0.011*
Controls					
GSEK (t-3)	0.5919	9.5067*		-3.2163	
	(0.7832)	(5.0119)		(4.0800)	
CUM_PAT (t-2)	-0.0003	-0.0040		0.0016	
	(0.0007)	(0.0044)		(0.0017)	
Year Dummies	*YES*	*YES*		*YES*	
N	*2057*	*980*		*1141*	
Chi2	*213*	*71*		*127*	
AIC	*4574.7703*	*1943*		*3135*	
BIC	4687	2041		3236	

Model results for North American assignees (NA), European assignees (EU) and Asian assignees (AS) subsamples. In columns 3 and 5 we test the null hypothesis that two coefficients are equal. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$