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Technological trajectories and environmental policy: the transformation of the automobile

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To my parents

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Chapter 1

Introduction

In the last few decades, technological change has received increasing attention in environmental economics studies (Jaffe et al., 2002) particularly due to the challenging persistence of global environmental problems and the inability to face them with current technology endowment (Popp et al., 2010).

It has long been argued that environmental technologies are inhibited by market forces and failures that do not provide the right stimuli to develop them. On the one hand, free-riding affects technological advances because in many cases who develops green technologies differs from who benefits from them. On the other hand, partially related to this first issue, double market failure exacerbates the propensity to invest in the development of environmentally-sound technologies (Jaffe et al., 2005). Indeed, eco-innovation, defined as "the production, assimilation or exploitation of a product, production process, service or management or business methods that is novel to the firm [or organization] 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, p.7), reduces negative environmental externalities that derive from economic activities and increases positive knowledge externalities typically associated with the creation of new knowledge and its appropriability. Due to differences in social and private returns, without policy intervention, firms are not incentivised to reduce their environmental impacts and increase their innovative efforts (Johnstone et al., 2010). In this direction, many scholars have investigated how eco-innovation responds to environmental policy from different perspectives. Even if this literature has provided evidence that green policy spurs eco-innovation (see Popp et al. (2010) for a detailed survey), it leaves aside some issues through which we can increase our understanding of endogenous technological change and how it can be redirected towards a sustainable path.

In this regard, our contribution aims to fill the gap in the literature by examining the relationship between technological trajectories and environmental policy in the automotive industry. The reasons that make the study of this industry appealing for our purposes are manifold. Firstly, the automotive industry has faced deep structural changes in recent decades, imposing a reconsideration of knowledge capital management (Laperche et al., 2011), especially during recent financial uncertainty. Secondly, the transport sector is one of the main sectors responsible for different environmental externalities such as traffic congestion and greenhouse gas (GHG) emissions (Timilsina and Dulal, 2011). In Europe, GHG emissions from the transport sector have experienced an increase of 24% between 1990 and 2008[1] and 94% of these emissions originates from road transport (EEA, 2011b). In addition, due to its high impact on local and global air pollution, a growing concern over automotive emissions is labelling the regulation of the automotive industry as a prior task in policy makers' agendas advocating the need to decrease the emission of pollutants released by vehicles. Thirdly, the increasing demand for low-emitting vehicles, together with stricter environmental regulations, has provided the incentives to develop new environmentally-sound

[1]When international aviation and navigation are included the percentage rises to 34%.

technologies that reduce vehicle emission levels. Indeed, since the beginning of the 20th century, the automotive industry has been characterised by the dominance of internal combustion engine vehicles. However, growing concern over vehicle pollutant releases has fostered the development of alternative low-emission vehicles that compete to become the car of the future. Finally, the industry is characterised by mass production of a limited number of products, short product life-cycles and the continuous introduction of modular innovation that enables the use of policy instruments that enhance environmental and safety performance (Bergek and Berggren, 2014).

What is more, in this complex scenario the literature adds the presence of three main sources of uncertainty that impact the innovation process. The first source is related to innovative outcomes, the success of which is defined through an ex post selection that cannot be predicted ex ante (Nelson and Winter, 1982). This is mainly due to bounded rationality for which the search process is substantially blind (Nelson and Winter, 1982) and is channelled into "satisficing" (Simon, 1956), instead of optimal, paths. Secondly, another source of uncertainty derives from future expected impacts of climate change and, therefore, on how policy will respond to them (Jaffe et al., 2005). Thirdly, which technology should substitute the established one represents an additional source of uncertainty in the automotive innovation process, because at the current stage the community of technologists is unable to identify the best alternative at least from both an economic and environmental perspective (Frenken et al., 2004).

Our contribution aims to investigate three main issues related to the effectiveness of environmental policies in triggering the development of alternative environmental technologies and unlocking the automotive system from fossil fuel path dependence. In doing so, the thesis employs patent data as indicator of technological activities. Even though we must be aware of their limitations, patents provide a wealth of information, available for long time series, on the inventions they protect (Archibugi and Planta, 1996), and their use in empirical studies is a widespread practice in the literature. Most importantly for the purposes of the thesis, among other information patent documents include the technological specification of each invention and citations to previous patents.

In this thesis, we first explore the inducement mechanism that underpins the interaction between environmental policy and green technological advances. Chapter 2 sheds some light in this direction by analysing whether environmental policy provides incentives to increase inventive activities in the environmental field. The majority of studies that investigate this relationship do not fully consider what influences technological change from a combined institutional and technological perspective. Thus, a study of the dynamic interaction between technological advances and policy makers 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 all the development costs) (Jaffe et al., 2005), all of which may reduce inventive performance, even if environmental policies are properly designed. To this end, we study under what conditions the European environmental policy portfolio and the intrinsic characteristics of assignees' knowledge boost worldwide green patent production. Using a fixed-effects negative binomial model our aim is to contribute to the related literature through (i) an analysis of a larger set of environmental policies, such as post-tax fuel prices, environmental vehicle taxes, CO_2 standards and European emission standards, (ii) an investigation of assignees' capability to anticipate the introduction and the tightening of emission standards pursuing inventions before their effective implementations, and (iii) an assessment of the worldwide effect of European environmental policy on patenting activities. In addition, as pointed out before, we test whether the potential stock of environmental knowledge and knowledge compositeness dynamics influence the propensity to develop green inventions. In order to measure these intrinsic characteristics of knowledge we employ the so-called Self-Organising Map (SOM) (Kohonen, 1982, 1990, 2001) 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. In addition, the distance between the mapped items can be measured and used as a proxy for their similarity and can be employed in empirical analysis. Therefore, applying this methodology, we first build a distance-based patent map where patents are mapped with respect to their technological classification codes in order to identify the main technological fields that characterise the automotive technology space. In a second application, the SOM is employed to detect the cognitive distance between assignees' knowledge base and measure the potential stock of environmental knowledge. That is, 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). Therefore, we map assignees using their inventive activities pursued in each previously defined technological fields and we measure the distance between their positions in the technology space. Finally, in the third application we run SOMs using European emission standards and their maximum thresholds of pollutants as input data. In this case, the distance among the items mapped is used as a proxy for the stringency of this policy instrument.

Moreover, the thesis aims to investigate the patterns of technological knowledge in the automotive technological system. Indeed, automotive technological knowledge has experienced drastic changes over the last decades. Since the 1970s, the dominance of internal combustion engine technology has been challenged by changes in the socio-economic framework described above that have impacted the stability of some technological trajectories characterised by cumulativeness in which discontinuity is discouraged.

An analysis of how technologies evolve represents a fundamental step in projecting future policy impacts (Popp et al., 2010) and assessing the effectiveness of past policy implementation. Therefore, in Chapter 3, we empirically investigate the dynamics of technological knowledge involved in technological trajectories assessing evolution patterns such as variation, selection and retention. We employ these elements as a lens for an ex post analysis that will allow us to explore how automotive technical knowledge evolved from 1970 to 2010 and define 'what' has been selected and retained. In doing so, we focus on electric and hybrid vehicles which are considered a viable technological path towards decreasing fossil fuel path dependence in the short and medium run (Frenken et al., 2004). Furthermore, recent efforts by policy makers to unlock the automotive technological system from internal combustion engine vehicles allow us to assess the effectiveness of environmental regulation in triggering the development of these alternative vehicles.

In doing so, we build a patent citation network that we exploit to measure variation and selection patterns in electric and hybrid vehicle technological knowledge evolution. The former is measured through the number of technological classification code combinations whereas the latter through the number of citations that these combinations received during time. Finally, in order to assess 'what' has been selected we apply two algorithms proposed by the literature on main path analysis that allow us to investigate large citation networks and identify the most selected part of the patent network. Furthermore, we calculate the Index of Knowledge Retention (IoKR) that we use, combined with the main path algorithms, to detect the most selectively retained knowledge in the network. This latter will allow us to observe the main technological components with an high degree of knowledge retention.

Finally, the thesis sheds light on the drivers that encourage a shift from incumbent internal combustion engine technologies towards low-emission vehicle technologies. Indeed, even if alternative technological trajectories provide improved environmental performance that is able to meet actual needs, evolutionary economists emphasise that the process of technology selection is path dependent, not predictable ex ante and irreversible, and thus, the market may select suboptimal technologies due to increasing returns to adoption (Arthur, 1989; Bruckner et al., 1996; Frenken et al., 2004). This conservatism of market selection, on the one hand, negatively affects the probability of adopting alternative technologies ('self-reinforcement') and, on the other, allows producers to take advantage of economies of scale and R&D investments (David, 1985). In addition to path dependence in technology adoption, Acemoglu et al. (2012) has stated that a path-dependent process characterises the type of innovation that is produced, providing incentives for firms that made innovative efforts in dirty technology in the past to innovate in dirty technologies in the future.

In addition, two main propositions are put forward from the literature on technological substitution (David, 1985; Arthur, 1989). First, even if substituting technologies are available and superior to the dominant one, technological substitution is not assured due to the presence of increasing returns to adoption. Second, in a technological substitution process in which a pool of new technologies competes for dominance, lock-ins into suboptimal technologies are possible due to path dependence of sequential adoption decision. In this regard, both propositions apply in the automotive industry, at least in part, due to the presence of competition between conventional and low-emitting vehicles and between alternative vehicle designs that may substitute conventional cars (Frenken et al., 2004).

In this complex framework where uncertainty, path - dependence and competition dominate, several authors highlight the fact that policy intervention may represent one of the main factors that allow socio-technical lock-ins to be overcome (Faber and Frenken, 2009; Rennings et al., 2013), and specifically, escape internal combustion engine vehicle lock-in (Cowan and Hultén, 1996). Therefore, Chapter 4 analyses which factors influence inventive activity dynamics by paying particular emphasis to the policy-driven crowding out effect.

Environmental policies lead to higher opportunity costs that derive from real resource requirements (financial and human resources) to develop and adopt alternative technologies needed to comply with policy requirements (Jaffe et al., 2002). Therefore, they are a potential source of crowding out where inventive efforts in environmental fields may drive away those in non-environmental technological domains. Apart from a few exceptions, this topic is almost unchartered and only a small portion of the debate is focused on the policy-driven crowding out effect. Moreover, the literature does not provide insights into the potential shift of inventive activities within the environmental domain, i.e. among alternative vehicles. Indeed, the study of *what* inventions come at the expense of other inventions represents a cornerstone in enlarging our understanding of the effectiveness of environmental policy in unlocking the automotive industry from fossil fuel. Indeed, the potential crowding out effect on non-green technological efforts may weaken fossil fuel lock-ins, whereas if green inventive activities crowd out other green technological efforts, the risk of locking-in technological change into a suboptimal substituting technology would be increased due to the absence of a better alternative technology. Hence, in this last chapter, we investigate whether environmental policy induces a shift from non-green to green inventive efforts and if policy implementation impacts competition between alternative vehicle technologies and also assess if environmental inventions drag away resources from the development of other environmental inventions.

In order to test these hypotheses we build a technology space using the abovementioned SOM technique. This methodology allows us to unpack the technological space into different technological fields. Thus, the resulting distance-based patent map is employed to measure the inventive efforts in each field. Once defined the technological fields that characterise the technology space, we employ a fixed-effects linear model through which we test whether tax-inclusive fuel prices, used as a proxy for carbon tax, and technological proximity between technological fields induce a shift from non-environmental inventions to environmentally friendly inventive activities and if they impact the competition between alternative vehicle technologies.

Chapter 2

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

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, CO_2 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 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 taking advantage of the knowledge produced by others (potential spillover pool). Finally, we observe that dynamic changes (both in quantity and in the number of technological fields engaged) in assignees' patent portfolios spur inventive performances.

2.1 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. 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., 2010).

Even if the related literature on the 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 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[1]. 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 chapter delves into what triggers green invention development, enclos-

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

ing both the European environmental policy portfolio and the intrinsic characteristics of knowledge (i.e. the potential stock of environmental knowledge and dynamic knowledge compositeness) in the analysis.

To do this, this study 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 analysis provides are manifold. Firstly, 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. To do that, we employ the so-called Self-Organising Map (SOM) (Kohonen, 1982, 1990, 2001) an unsupervised Neural Network (NN) technique able to detect similarities in multidimensional data and represent them in a two-dimensional space where a global 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 detected the winning map node (i.e. the node with the lowest ED), the learning process allows the map to become 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, whereas less similar ones are mapped farther away from each other (Kohonen, 2013).

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 specific and relative characteristics of their multidimensional input data. Most importantly, the distance between the mapped items can be measured and used as a proxy for the similarity of input data and can be employed in empirical analysis. Indeed, in the first application, we use patents and their technological classes to build a distance-based patent map that allows us to identify the technological domains that characterise the automotive technology space. The distance between patents is then used as a proxy for their technological relatedness in order to obtain technological clusters. In the second application, we run the SOM using as input data the distribution of patents filed by each assignee in each specific technological field defined in the previous SOM exercise. The distance between assignees is used as a proxy for the similarity of assignees' knowledge base. Finally, in the third application the input data are European emission standards and their maximum thresholds of pollutants. In this case, the distance among the items mapped is used as a proxy for the stringency of this policy instrument.

Secondly, we investigate whether firms 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 chapter 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 chapter is structured as follows: Section 2.2 presents the related literature on both the innovation impact of environmental policy instruments and the knowledge characteristics that spur innovative performances. In Section 2.3 we describe the methodological framework through which the independent variables are built. Section 2.4 introduces the empirical model, Section 2.5 describes the results, and finally, Section 2.6 concludes.

2.2 Theoretical background and provable hypotheses

2.2.1 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; Rennings, 2000).

Popp et al. (2010) surveys 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) finds a positive correlation between pollution abatement control expenditures (PACE) (used to proxy regulatory stringency) and R&D spending, but it does not observe any effect of this policy instrument on patent activity. On the contrary, the results of Brunnermeier and Cohen (2003) provide evidence on a positive relationship between green patents and PACE.

In a recent comparative study between the automotive and energy sector, Bergek and Berggren (2014) explores whether different environmental policy instruments supported different types of innovations. The study 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 and Berggren (2014) highlights that general economic instruments (e.g. CO_2 taxes, ETS, etc.)

boost incremental innovation while general regulatory instruments (such as emissions regulation) trigger modular innovation. Finally, technology-specific instruments are suitable to spur the development of radically new technologies.

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 and Berggren, 2014). The literature related to general economic instruments in the automotive industry has mainly examined the effect of fuel prices on boosting the development of low-emitting technologies. Aghion et al. (2012) analyses the effect of tax-inclusive fuel prices on patent activities across worldwide firms. The results provide insights into 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 also explores what spurs innovation beyond fuel prices. This class of polices (e.g. registration taxes, purchase taxes and subsidies, etc.) are scrutinised in Klier and Linn (2012), who discusses the role of such instruments in promoting cars registrations and average vehicle CO_2 emission rates. While the authors find that these taxes have a significant negative effect on new vehicle registration, their analysis provides little evidence on the decrease in long-run vehicle emission rates. However, the majority of the studies investigate the effects of an environmental policy portfolio 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.

Furthermore, the literature acknowledges that, together with economic instruments, another type of environmental polices can be implemented to boost technological change, i.e. regulatory instruments. This broad range of regulatory policies influences firms actions by prescribing specific technological solutions (technology standards), by establishing an upper threshold to emission level (emission standards) or by imposing maximum limits of emissions per unit of output (performance standards) (Bergek and Berggren, 2014). In the automotive industry the main general regulatory instruments are performance-based standards such as, fuel economy, CO_2 and noxious emission standards. As far as the former is concerned, Clerides and Zachariadis (2008) holds that the introduction or adoption of more stringent fuel economy standards and fuel prices improves new-car fuel efficiency. In addition, the authors observe that in Europe and Japan fuel economy standards have a greater impact than fuel prices. In another noteworthy study, Hascic et al. (2009) analyses how fuel prices, emission standards and on-board diagnostic systems of one country affect automotive green patent activities in the others. The results of the study show that green inventions are impacted in a greater and positive way by foreign regulation than domestic standards.

Lee et al. (2011), underlines the positive effect that US technology-forcing auto emission standards have on innovation in the automotive industry between 1970 and 1998. The results highlight that auto makers and components suppliers innovate in advanced-emission control technologies for automobile applications when the unit cost of auto emissions control devices per car increases, 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).

Economic uncertainty can threat firm' investment decisions (Pindyck, 2007). This is particularly true when investments regard R&D activities, the success 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., 2010).

Whereas environmental policy stringency has been analysed in several papers, the effect of policy predictability remains substantially unchartered at least from an empirical perspective. Söderholm et al. (2007) ascribes 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) highlights 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) points out that car makers anticipated CO_2 restriction reducing emissions when the EU legislation has been announced (2008) instead of waiting for its implementation (2012-15).

Our objective is assessing whether general regulatory policies, such as CO_2 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 question whether environmental policies impact on the diffusion of environmentally sound technologies (Lanjouw and Mody, 1996; Popp, 2006; Dechezleprêtre et al., 2008). This branch of literature focuses 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 provides clear evidence that absolute environmental policy stringency induces the transfer of green technologies. Only recently, (Dechezleprêtre et al., 2012) underlines the role played by relative regulation stringency on the transfer of environmentally sound technologies between recipient and source countries.

These works pay 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)) analyse the direct relationship between domestic environmental regulations and foreign production of eco-innovation. The focus, in this chapter, is no longer the transfer of technologies produced abroad, but inventions produced in foreign countries to directly comply with foreign regulations, e.g. the Japanese firm that develop 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.*

2.2.2 Supply-side factors and innovation

Even though environmental policy impacts 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 is highlighted by Popp (2002), in which the links between past and current research on energy-efficiency innovation are analysed. The results show that the existing base of scientific knowledge, together with energy prices, trigger energy-efficiency innovation. In addition, the author accounts for the quality of knowledge stock through patent citations, finding that the usefulness of the available stock of knowledge assumes importance in shaping eco-innovation.

Another paper that combines supply-side factors and environmental policies is Aghion et al. (2012). The authors test the hypothesis that directed technical change hampers 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 provides evidence (using aggregate spillover and firms' own stock of inventions) of path dependence in the type of innovation pursued.

This chapter 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 captures the similarity between firms patent stocks, Jaffe (1986) finds that R&D productivity is enhanced by the R&D output of those firms that had a closer technological position within the technology space, i.e. the potential spillover pool. 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.*

2.3 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, we use patent data as a proxy for invention. 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, p.214). However, 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 use Cooperative Patent Classification (CPC) [2] 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[3]. We retrieved 30,348 patents filed to European patent offices (including the European Patent Office (EPO)) from 1990 to 2012.

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 avoids the inclusion of duplicated patents. Firstly be-

[2]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.

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

cause our focus is on inventive processes rather than on the analysis of what drives inventions' diffusion. Secondly, to test Hypothesis 3, we require 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[4] 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 retrieved 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[5] we included it in our dataset. The final result is a dataset that, after considering co-patenting[6] and removing observations with missing values (some of the patents had no assignee name, application country, etc.), accounts for 28,917 patents, with a total of 4,942 assignees from EU and non-EU countries.

2.3.1 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 $F = (F_1...F_k)$ where F_k is the firms' efforts devoted to the k-th technological area (Jaffe, 1986).

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

[5]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

[6]Some patents are developed by more than one assignee together. We consider the co-patented invention as a single patent for each assignee.

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 employ an unsupervised neural network (NN) technique, named Self-Organising Map (SOM) (Kohonen, 1982, 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, 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 (distant) in the final output map.

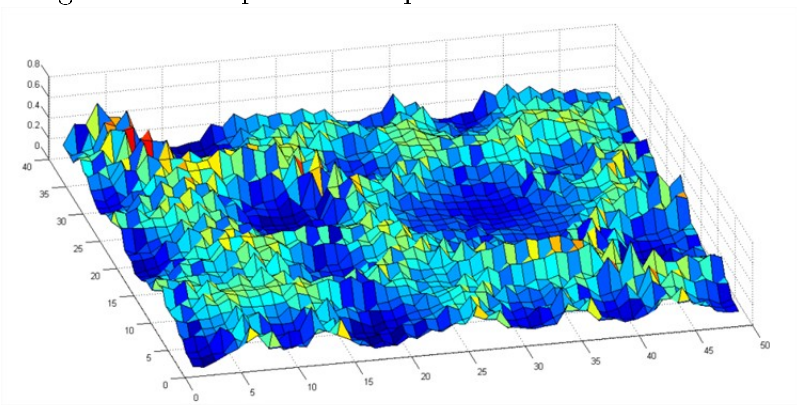
In this first application of the SOM, we create a patent map (PM) using co-classification of 4-digit CPC classes assigned to each patent. The assumption is that the presence of the same CPC classes in two patents can be used as a proxy for the strength of the patents' technological relatedness.

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 employ them to identify the similarity between patents' technological content. In this case the input data of the SOM is structured as follow: each column represents the frequency of 4-digit CPC classes assigned to each patent, while rows the patent ID:

	CPC_1	CPC_2	$\dots$	CPC_m
$Patent_1$	$\dots$	$\dots$	$\dots$	
$Patent_2$	$\dots$	$\dots$	$\dots$	
$\dots$	$\dots$	$\dots$	$\dots$	
$Patent_n$	$\dots$	$\dots$	$\dots$	

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). The output of the SOM (Figure 2.1) is a PM where the patents that provide similar (different) technological improvements are placed closer (distant) (exemplified in Figure 2.2). Finally, using a k-means algorithm (MacQueen et al., 1967), we detected 20 technological clusters[7], to which each patent had been assigned through the SOM (Figure 2.3).

Figure 2.1: SOM represented as a Unified-distance Matrix using patent classes assigned to each patent as input data

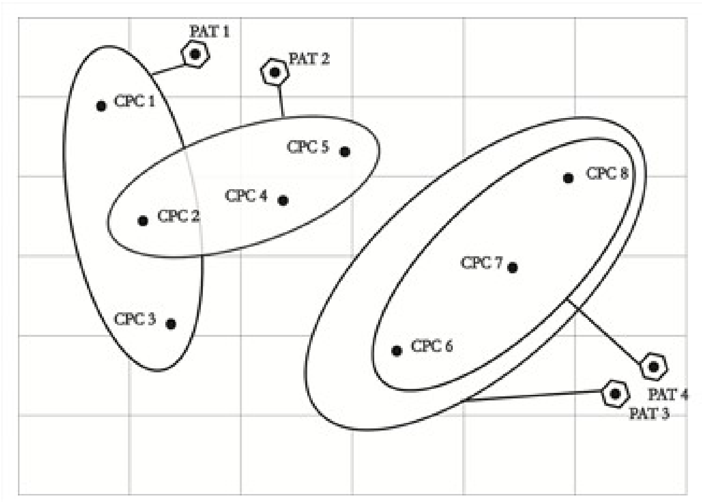


The vertical axes as well as the colour return the distance between a node and its closest neighbour.

Source: own elaboration

[7]The k-means is run multiple time 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).

Figure 2.2: Example of patent map created through 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 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 CPC class).

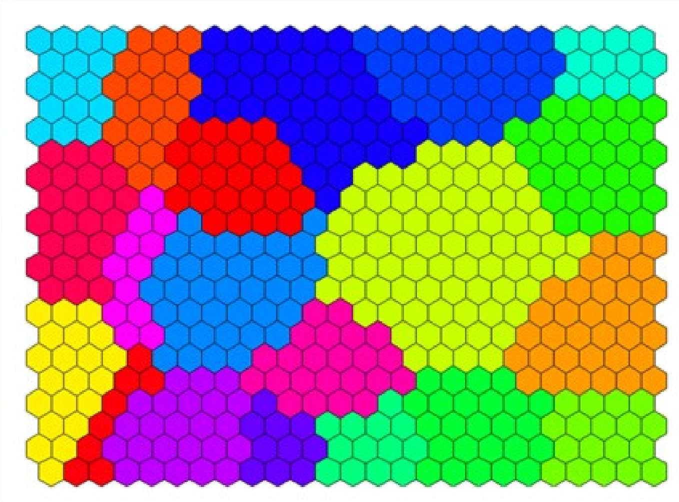
Source: own elaboration

2.3.2 Supplied-side variables

Once the k technological areas are identified, we run the SOM to obtain the similarities across assignees' innovative efforts. In this second 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 farther away).

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

Figure 2.3: Clustering results of the SOM map using k-mean algorithm



Each color corresponds to a cluster of nodes
Source: own elaboration

	Battery	Internal 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 farther 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:

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

where $EPAT_{j,t}$ are environmental patents filed by another 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 grows, and decreases when the distance increases. In order to remove the effect of the total number of firms that patented in each year, we divided 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[8].

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 track 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.

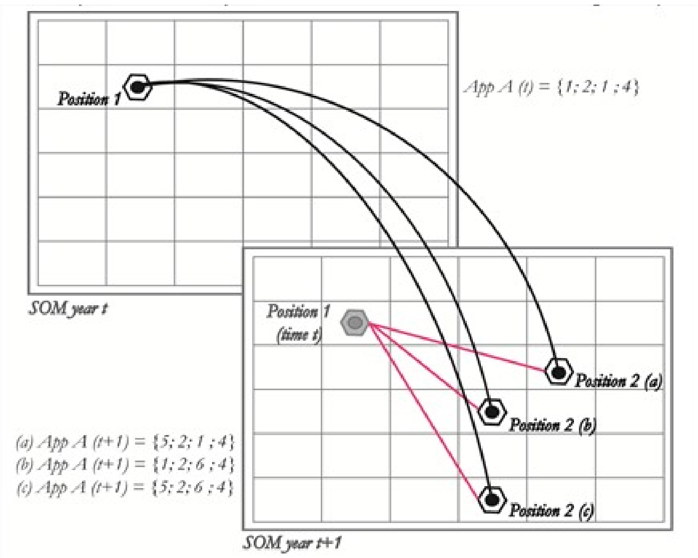
Note that an applicant's position on the map is defined by the inventive efforts pursued in each technological field k. Thus, we point out that assignees change their positions on the map as a result of changes in their knowledge compositeness (an example is provided in Figure 2.4). In this way, the process captures ex-post changes in knowledge compositeness within

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

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.

Figure 2.4: 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.

Source: own elaboration

2.3.3 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.

General economic instruments

Fuel prices are some of the main drivers of environmentally-friendly technologies in the automotive industry (Hascic et al., 2009; Aghion et al., 2012). We use IEA (International Energy Agency) data on post-tax gasoline prices[9] for households in the EU. Figure 2.5 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 on. In addition, we can observe from Figure 2.5 that total average fuel taxes follow a similar trend, though with a lower decrease during the 2008-09 years.

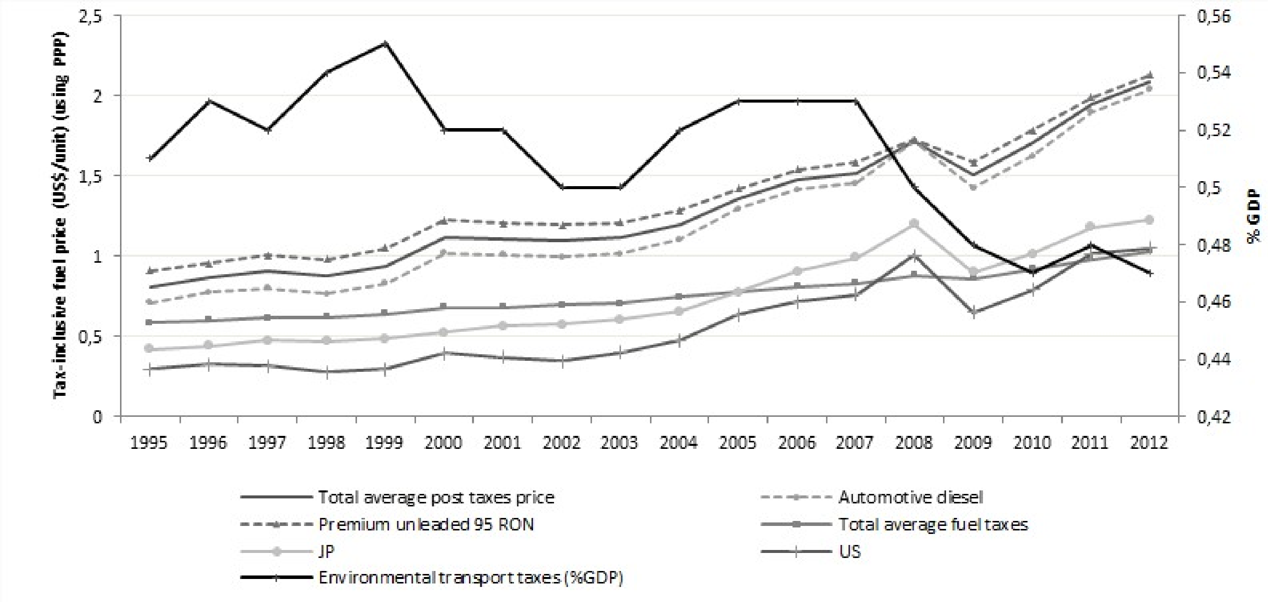
Since our dependent variable (i.e. annual count of patents filed by each assignee) has assignee-level variation that we want to exploit, we weight tax-inclusive fuel price by the relative importance of country c for assignee i. Following Aghion et al. (2012) we assume that the importance of each European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

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

where $F\_PR_{c,t}$ is the tax-inclusive fuel price for country c and $w_{i,c}$ is a time invariant weight related to the share of

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

Figure 2.5: 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)

patent of assignee i in country c in the period 1990-1997[10].

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 oneoff 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[11]. Figure 2.5 also shows the

[10]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.

[11]This data is also available for environmental taxes levied on road transportation, that mainly includes vehicle ownership, vehicle use, other transport equipment and

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:

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

General regulatory instruments

In the European automotive industry, emission standards are introduced through directives and regulations as shown in Table 2.1. We observe from the right columns of Table 2.1, 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.

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, 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

related transport service taxations, other than fuel taxes (Eurostat, 2001).

Table 2.1: 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

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 2.6a 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.

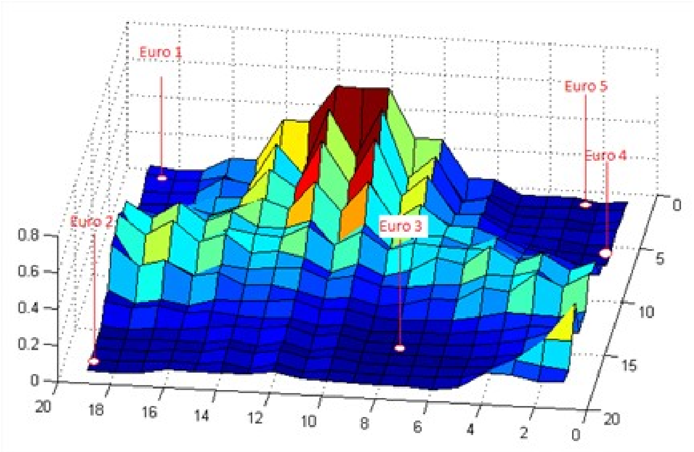
From this map we obtained a continuous variable (STD) where the distance between these nodes is used as a proxy for the stringency of the European emission standards. Using node distances, we miss the first observation related to Euro 1 (1992). However, this does not impact the reliability of our study that focuses on the years between 1997-2010.

Furthermore, the maximum levels of allowed pollutants release decrease over time. Thus, we employ this variable as a proxy for emission standards upper limits (Figure 2.6b).

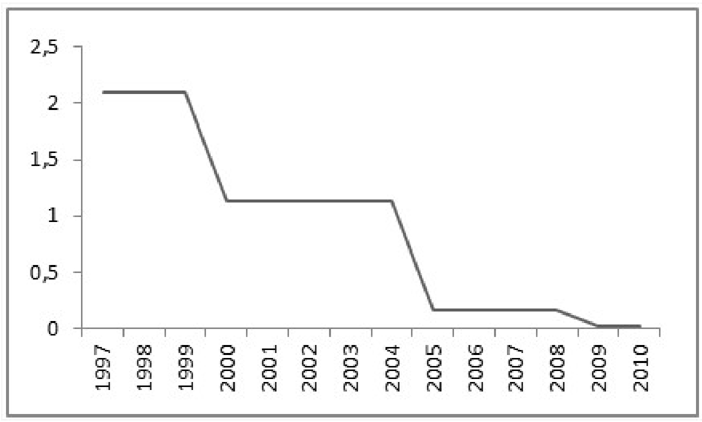
Figure 2.6b clearly shows that our continuous variable captures the higher stringency of European emission standards. In order to test whether assignees anticipate the introduction of the policies pursuing inventive activities before their effective implementations, we build the variable using the year of announcement of each European emission standards. The variable is defined as follow:

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

Figure 2.6: STD variable



a. 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)



b. Cumulative nodes distance from 1996 to 2010.

Source: own elaboration

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 CO_2 targets introduced through voluntary commitment by the European Commission. 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). In our time span (1997-2010) we just record one change of the upper limit of CO_2 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 CO_2 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 CO_2 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 CO_2 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:

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

Where $\gamma_{i,c}$ is the share of new vehicle registrations in country c (EUROSTAT, 2013) and $CO2\_T_{EU,t}$ is the European upper limit to CO_2 emissions.

2.3.4 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 potential 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'.

2.4 Empirical model

We used the following empirical model to test our hypotheses:

$$lnEPAT_{i,t} = \beta_1 F\_PR_{i,t-1} + \beta_2 VEH\_T_{i,t-1} + \beta_3 STD_{i,t} +$$

$$+\beta_4 CO2_{i,t} + \beta_5 PSEK_{i,t-3} + \beta_6 KC_{i,t-1} + C_{i,t-1} + \alpha_i + Z_t + \varepsilon_{i,t}$$

where the dependent variable $EPAT$ is the annual count[12] 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 CO_2 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

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

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 apply a fixed-effects negative binomial model to estimate the equation above (Cameron and Trivedi, 2013). 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).

2.5 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 2.4). Table 2.2 reports the descriptive statistics, while Table 2.3 shows the correlation matrix and the Variance Inflation Factors of each variable.

2.5.1 Policy inducement mechanism

The results related to the full sample of assignees, shown in Table 2.4 (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

Table 2.2: Descriptive statistics

	Mean	SD	Min	Max
E_PAT	3.054	14.290	0	341
ln F_PR	.214	.197	-.207	.750
ln VEH_T	-.748	.216	-1.620	.270
ln CO2	4.151	.500	-.196	4.941
ln STD	-2.297	1.533	-7.589	.128
PSEK	.337	.526	0	11.243
KC	.9827679	2.126	0	29.771
GSEK	.205	.143	0	.437
CUM_PAT	199.873	192.813	0	619

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 regu-

Table 2.3: 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	-0.08	1						
ln CO2	1.05	.952	0.02	0.03	1					
ln STD	3.55	.281	-0.83	0.03	-0.06	1				
PSEK	1.02	.982	0.002	-0.00	0.01	-0.01	1			
KC	1.03	.967	0.04	-0.06	0.02	-0.02	0.12	1		
GSEK	2.70	.369	0.02	-0.18	0.16	-0.09	0.03	0.11	1	
CUM_PAT	2.93	.341	-0.22	-0.07	0.19	0.05	0.01	0.09	0.76	1
Mean VIF	2.16									

lations 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.

In order to test Hypothesis 3, we built different samples relative to the geographical location of the assignees[13]. Columns 2 and 3 (European and extra-European assignees respectively) of Table 2.4 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 CO_2 standards impact inventive activities

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

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, North America and Japan) we can notice that fuel prices have always been higher in Europe than in the other two geographical areas (Figure 2.5). Indeed, comparing the F_PR coefficients between the three sub-samples (Table 2.5) 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 2.4, the whole set of European policy variables impact European assignees, while only a portion of them influence patenting activities in both sub-samples.

2.5.2 Innovation supply-side factors

Table 2.4 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.

2.6 Conclusions

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 CO_2 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 this chapter 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.

Table 2.4: 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***	2.5298*	5.8484***	χ^2 = 12.56***
	(0.9723)	-13.051	-15.744	Prob > χ^2 = 0.000
ln VEH_T (t-1)	0.8896***	1.1297***	0.4826	= 3.04*
	(0.2958)	(0.3913)	(0.4882)	Prob > χ^2 = 0.081
ln CO2	-0.3019***	-0.3122*	-0.2535	= 0.00
	(0.1170)	(0.1651)	(0.1763)	Prob > χ^2 = 0.976
ln STD	-0.4082***	-1.2154***	-0.2692*	= 8.53***
	(0.1039)	(0.3197)	(0.1432)	Prob > χ^2 = 0.003
PSEK (t-3)	0.2311***	0.3942***	0.1036*	= 7.19***
	(0.0448)	(0.0678)	(0.0622)	Prob > χ^2 = 0.007
KC (t-1)	0.0764***	0.0864***	0.0642***	= 2.66
	(0.0059)	(0.0083)	(0.0087)	Prob > χ^2 = 0.103
Controls				
GSEK (t-3)	0.7761*	0.5919	1.8479***	
	(0.4140)	(0.7832)	(0.7091)	
CUM_PAT (t-1)	0.0000	-0.0003	-0.0003	
	(0.0002)	(0.0007)	(0.0004)	
Year Dummies	YES	YES	YES	
N	4226	2057	2169	
Chi2	334	213	154	
AIC	9720.7	4574.7	5138.9	
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 2.5: 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*	$\chi^2 = 0.22$	3.8553*	$\chi^2 = 23.35$***
	-13.051	-26.175	Prob > $\chi^2 = 0.640$	-21.478	Prob > $\chi^2 = 0.000$
ln VEH_T (t-1)	1.1297***	11.520	$\chi^2 = 0.01$	0.3814	$\chi^2 = 6.57$**
	(0.3913)	(0.7596)	Prob > $\chi^2 = 0.907$	(0.7348)	Prob > $\chi^2 = 0.0104$
ln CO2	-0.3122*	0.3173	$\chi^2 = 1.21$	-0.3461	$\chi^2 = 0.26$
	(0.1651)	(0.3400)	Prob > $\chi^2 = 0.271$	(0.2215)	Prob > $\chi^2 = 0.609$
ln STD	-1.2154***	0.2557	$\chi^2 = 0.05$	-0.5334***	$\chi^2 = 16.77$***
	(0.3197)	(0.2797)	Prob > $\chi^2 = 0.828$	(0.1756)	Prob > $\chi^2 = 0.000$
PSEK (t-3)	0.3942***	0.0520	$\chi^2 = 6.00$**	0.1214	$\chi^2 = 4.75$**
	(0.0678)	(0.1020)	Prob > $\chi^2 = 0.014$	(0.0821)	Prob > $\chi^2 = 0.029$
KC (t-1)	0.0864***	0.1257***	$\chi^2 = 2.62$	0.0421***	$\chi^2 = 6.33$**
	(0.0083)	(0.0193)	Prob > $\chi^2 = 0.105$	(0.0109)	Prob > $\chi^2 = 0.011$
Controls					
GSEK (t-3)	0.5919	9.5067*		-32.163	
	(0.7832)	-50.119		-40.800	
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	4574.7	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

Chapter 3

Variation, selection and retention patterns in technological knowledge evolution: the case of electric and hybrid vehicles

Abstract: This chapter aims to investigate the dynamics of electric and hybrid vehicle technological advances through patterns of technological evolution, i.e. variation, selection and retention. To do this, we apply a methodological framework based on patent citation network and patent technological classes. We also map the main directions in which development of these technologies has moved, combining main path analysis with a knowledge retention index that weights citations by the knowledge retained among patents.

This approach allows us to recognise technological knowledge that has been selected and retained over time and emphasise the trends in variation and selection. Our findings suggest that the evolution of electric and hybrid technological knowledge went through an outstanding explorative phase during the 1990s in which variation increased, followed by an increase in selection that can be interpreted as the beginning of an exploitative phase.

3.1 Introduction

An overwhelming body of literature acknowledges that technological advances should be understood through an evolutionary processes (Nelson and Winter (1982); Basalla (1988); Mokyr (1990); Dosi and Nelson (1994); Ziman (2000); among others). The analogy with biological evolution is pointed out and resides on the concept of 'blind variations selectively retained' (Campbell, 1960) through which elements such as variation, selection and retention can be used to explain the dynamics of technology.

Even though there is a strong similarity between these processes (i.e. biological and technological evolution), the extent to which evolutionary theory is applicable to the technological context is somewhat blurred. It has been argued that the process underpinning the evolutionary theory of technology is Lamarckian, instead of being Darwinian or neo-Darwinian. Indeed, the required 'blindness' in variation creation that characterises the latter fails in a Lamarckian evolutionary model and in technology evolution, the variations offered to the selection environment are 'directed' towards the selection process (Nelson, 1994). In other words, variations are directed towards the creation of technologies that are fit to endure (Schot and Geels, 2007).

Focusing on the cumulative nature of technological advances, the aim of this study is to shed light on the evolution of technical knowledge related to electric and hybrid vehicles (EVs, HVs), an alternative technological trajectory that is challenging the dominant internal combustion engine (ICE) design. To do this, we use the evolutionary framework of analysis described above, assessing evolution patterns such as variation, selection and retention and building on a methodological framework based on patent network analysis and patent technological classes. Although we are aware that the analogy between technologies and biological organisms is limited by several factors that we will explore in the next section, we use these elements as a lens for an ex post analysis that will allow us to explore how automotive technical knowledge evolved from 1970 to 2010 and define 'what' has been selected and retained. What makes the study of these technologies so appealing for our purposes is the presence of two main technological paths that drive vehicle propulsion systems towards the achievement of environmental objectives and the competition between them. We have, on the one hand, the greening of the dominant design, i.e. the internal combustion engine vehicle (ICEV), and the development of alternative low-emission vehicles (LEVs) on the other, i.e. hybrid, electric and fuel cell vehicles.

What is more, environmental and innovation policy impact technological regimes and demand conditions (Oltra and Saint Jean, 2009a). In turn, the policy framework is conditioned by these two elements due to the acknowledged co-evolutionary relationship that characterises technology, institutions and industrial structure advance (Nelson, 1994). In this regard, the automotive industry has been challenged, over the last few decades, by growing concern over its environmental impact. Environmental policies have provided incentives to develop a variety of technologies that may represent valid solutions in the short run (e.g. hybrid and electric vehicles) as well as in the long run (e.g. fuel cell vehicles fuelled with hydrogen) (Frenken et al., 2004). However, the related literature has provided little evidence on the knowledge base and learning process that characterise the development of environmental technologies (Oltra and Saint Jean, 2009a), especially when they compete to become an alternative for substituting established technologies. In this complex scenario, three main sources of uncertainty impact the innovative process. The first source is related to innovative outcomes, the success of which is defined through an ex post selection that cannot be fully predicted ex ante (Nelson and Winter, 1982). This is mainly due to bounded rationality for which the search process is substantially blind (Nelson and Winter, 1982) and is channelled into satisficing (Simon, 1956), instead of optimal, paths. Secondly, another source of uncertainty derives from future expected impacts of climate change and, therefore, on how policy responds to them (Jaffe et al., 2005). Finally, there is uncertainty over what technologies should substitute the established one, because the best alternative vehicle technology cannot be identified at this stage, at least from both an economic and an environmental perspective (Frenken et al., 2004).

In Section 3.2 we provide a brief overview of the different technological evolution theories that has been proposed in recent decades (Basalla, 1988; Mokyr, 1990, 1996). Using these theories, we propose an analogy between technological and biological evolution through which we hypothesise that technological knowledge proceeds through the main mechanisms that steer the evolution of organisms, i.e. variation, selection and retention.

In Section 3.3 we present the methodological framework. As far as variation is concerned, we identify the number of technological class combinations proposed by the community of inventors each year. We then use citations among these combinations to assess technological knowledge selection.

In addition, we present the two algorithms proposed by the literature on main path analysis that we employ to investigate large citation networks and identify the most selected part of the patent network. The main path analysis helps us to examine 'what' knowledge has been selected. Furthermore, in this section we describe how we calculate the Index of Knowledge Retention ($IoKR$) that we employ, combined with the main path algorithms, to detect the most selectively retained knowledge in the network. This latter will allow us to observe the main technological components with a high degree of knowledge retention.

Section 3.4 describes the technology examined in the chapter and highlights the most important historical events that influenced its knowledge pattern. Finally, Section 3.5 presents the results while Section 3.6 offers a conclusion.

3.2 Theoretical framework

3.2.1 Technological evolution theories

Many studies have highlighted that technology evolves (Basalla, 1988; Nelson and Winter, 1977; Ziman, 2000; Mokyr, 1990; Vincenti, 1990) and, although to different extents, that there is an analogy between biological and technological evolution. Before exploring the theories that propose this analogy to explain technological evolution, it is fundamental to delve into the principles and concepts that characterise evolution in biological systems. In this regard, Brey (2008) summarises the main building blocks formulated by Darwin (1859) in the Origin of Species. The first principle, i.e. *phenotypic variation*, implies the presence of a trait variety that characterises organisms in a species, e.g. eye colour. In evolutionary terms, part of the variation between individuals in species is heritable from one generation to the next (*heritability*), i.e. 'offspring will tend to resemble their parents more than they do other individuals in the population' (Brey, 2008). Individuals are also characterised by *differential fitness*, implying that there are organisms that adapt better to an environment and are more likely to survive and reproduce than others.

The mechanisms that drive these principles can be summed up as *genetic reproduction, mutation and recombination.* The former points out that traits pass on to subsequent generations through reproduction of the genotype, whereas the latter, i.e.

mutation and recombination, affect the creation of variants. Finally, biological evolution implies *blindness* in variation and selection processes, meaning that premeditation and learning from the past are avoided.

Built on these principles, evolution by natural selection leads to the retention, in future generations, of traits that better adapt to the selection environment. Consequently, an increasing number of individuals will be equipped with those traits.

In the literature on technological change, different attempts have been made to adapt these principles to technology dynamics.

Focusing the analysis on artefacts as a unit of observation, Basalla (1988) explains the process of technological innovation. The author compares artefact types to biological species and particular elements that constitute the artefactual realm to individuals of the species. Therefore, in his view, hammer is the species and the different types of hammer are the individuals that vary in traits. Although artefacts do not reproduce, they undergo a process of heritance in which the same or similar versions of the artefact are passed on to future generations. Basalla points out that in technological evolution, selection operates as a driving force in choosing variants that are used and reproduced (those that fit better into the selection environment) and those that are executed.

Based on a distinction between useful knowledge and techniques, Mokyr (1990, 1996, 1998, 2000) argues that the focus of the analysis of technological change should be devoted to the evolution of technological knowledge rather than focusing directly on artefacts. Useful knowledge is considered the underlying structure (genotype) whereas techniques, that represent instructions about 'how to do things', are the manifestation of useful knowledge, analogous to the phenotype. Variation occurs through the creation of 'useful knowledge' and techniques are the units of selection. Thus, selection arises when the utilisation of a technique occurs, assuming that when a particular technique is used, it is reproduced.

However, these theories reveal several dissimilarities between biological and technological evolution for which the comparison between the two remains at the level of analogy or metaphor. These issues particularly regard the human behaviour that underpins variation and selection processes in technological change, implying the absence of *blindness* caused by the consciousness of human choices. This feature tells us that the process of technology evolution should be considered as Lamarckian, rather than Darwinian. Although the Lamarckian evolutionary model has been abandoned in biology, there are insights that the theories of technological evolution, formulated by different scholars, imply that acquired traits are passed on to future generations.

In addition, the analogy with living specimens fails when we observe that, whereas artefact types (species) interbreed, this does not happen in biological species. Moreover, Basalla's theory involves the reproduction of the artefact but there is no equivalent of genes that are inherited. On the other hand, as far as Mokyr's theory is concerned, knowledge can exist without the vehicles that maintain it, whereas in biology, genes cannot exist without living organisms.

3.2.2 A proposed view of technological evolution

Far from proposing a new theory of technology evolution, our study simply suggests an analogy between biological and technological evolution using the former as a metaphor to explain the latter. The objective of this approach regards the identification and analysis of the main mechanisms through which technologies evolve, i.e. variation, selection and retention. In particular, in this ex post analysis of technological knowledge evolution, we are interested in exploring and assessing 'what' has been retained or discarded during this process.

The focus of our analysis is technological knowledge that characterises technological trajectories. Indeed, discovery and creation, involved in the solution of specific problems, are associated with the process of technological innovation (Dosi, 1988). In this regard, technological paradigms (Dosi, 1982, 1988; Nelson and Winter, 1982)embody the 'set of understandings' that drive technological advances, involving specific heuristics that are shared by the community of practitioners (e.g. firms, technical society, etc.) to 'make things better' (Dosi and Nelson, 1994). These two concepts are linked in the words of (Dosi, 1988), i.e. 'a technological paradigm can be defined as a "pattern" of solution of selected techno-economic problems based on highly selected principles derived from the natural sciences, jointly with specific rules aimed to acquire new knowledge and safeguard it, whenever possible, against rapid diffusion to the competitors' (Dosi, 1988, p.1127).

In this framework, different technological opportunities that characterise each technological paradigm can be undertaken, the realisation of which defines technological trajectories that in turn change the techno-economic characteristics of the technology and its production process (Cimoli and Dosi, 1995). In principle, within each trajectory, technological knowledge tends to be cumulative and incremental, excluding more radical improvement and discontinuities.

In this analysis we consider technological trajectories as species that evolve through the evolution of their entities that are, in this case, single pieces of technological knowledge able to provide technological advances.

From this point of view, patents are comparable to 'individuals' of the species. Patents have been widely used to measure knowledge production (Griliches, 1979, 1990). They include a wealth of information that is widely exploited to increase our understanding of technological change. Each patent provides a detailed description of the technical content of each invention through structured and unstructured items that form patent documents. Following Tseng et al. (2007), the former refers to information that is uniform in semantic and format across patents (e.g. date, publication number, priority country, etc.), whereas the latter refers to text free fields (e.g. title, abstract, claims, etc.). As far as the first is concerned, patent documents are classified through a set of technological classes, assigned by both the inventor and the examiner of the patent office, that allow patents to be identified within specific technological domains[1]. The second refers to the description of the invention and therefore to what a patent claims. Recalling the main evolutionary building blocks through which a system evolves, we assume that the technological classes assigned to patents play the role of genes in biological organisms. Furthermore, due to the fact that the genotype, which records the underlying structure of the units, is connected to the manifested entity (i.e. the phenotype), we identify in the specific patent claims (the technicalities of the invention), the observable traits of the genes which undergo the selection environment. Using patents as a unit of analysis, we are close to Mokyr's view of technological evolution in which knowledge, instead of artefacts, evolves.

Once we have defined the unit of selection (technological classes), we need to identify the two main mechanisms that characterise evolution, i.e. variation and selection. The pattern of variation is involved in the problem-solving purpose of innovative activities (Dosi, 1988). In each generation, different solutions to different (technical) problems are proposed for selection. Using patents as individuals enables us to view variation as the creation of technical knowledge combinations included in patents, i.e. combinations of technological classes. It is noteworthy that the manifestation of this underlying struc-

[1] Some of the most important classification systems are: Cooperative Patent Classification (CPC), International Patent Classification (IPC), United States Patent Classification (USPC).

ture (what each patent claims) varies according to each combination of technological classes that will be retained if it fits into the selection environment.

The selection process here implies that a variation of technological knowledge is selected and passed on to future generations. Therefore, we proxy the selection process with citations among patents. Following the 'stand on giant's shoulders' feature of citations, we assume that the knowledge included in patents is selected when following patents cite previous ones. However, unlike biological organisms in which genetic information is transmitted from parents to offspring, although some of the citing patents may inherit the whole set of technological classes, others may just retain some or none of them.

The limitations that characterise the abovementioned theories can also be observed in our proposed view of understanding technological evolution through patent data. In fact, we do not claim a complete overlap between the two concepts, but we use this analogy as a metaphor to analyse technological evolution and its patterns. Indeed, the fact that patents are filed to protect firms' economic and technical performance and enhance competitive advantage, highlights that the production of new knowledge is directed towards fitting into the selection environment, i.e. variation is not random and blind. Furthermore, if knowledge is not retained in the subsequent generation, this does not imply that it cannot be used by following generations. This is in contrast with the biological paradigm in which extinction is irreversible (Mokyr, 2000).

3.2.3 Variation and selection in emerging technologies

An important element that evolutionary theories build on is the selection environment. Nelson and Winter (1982) identify markets and their economic and regulatory requirements as the main selection forces. The selection environment is subsequently enlarged by Basalla (1988) who emphasises the presence of economic, military, social and cultural factors as driving forces in the selection process.

As stated before, technological variation and selection are not independent processes because the former is directed towards the latter, due to the creation of a set of variants that should fit the selection environment in order to be retained in future generations. This is particularly true when we deal with emerging technologies. In this regard, Bakker et al. (2011) highlight the role of expectations in promising technological options for two types of actors. On the one hand, there are the ones that propose variations (enactors) and, on the other hand, the ones that select and favour some of them (selectors). These actors meet in the 'Arena of expectations' in which the expectation interaction of both drives 'the coordination of research activities, the selection of technologies and their further development for market introduction' (Bakker et al., 2011).

However, even if the analogy with biological evolution is limited by this issue, variation and selection processes are extremely important in understanding knowledge patterns. Indeed, these two elements are connected to the concepts of exploration and exploitation (March, 1991) that are mutually related and build on each other (Nooteboom, 2000).

It is widely acknowledged that knowledge recombination provides novelty (Schumpeter, 1939; Nelson and Winter, 1982; Olsson, 2000; Fleming and Sorenson, 2001) and that technological knowledge is characterised by a recombination of new or existing pieces of knowledge (Krafft et al., 2011).

However, even if the number of possible combinations and their conflation is essentially infinite, only a part of them is explored (due to bounded rationality). In order to reduce uncertainty, localness characterises the search process limiting recombination to familiar bits of knowledge and the improvement of existing ones (Fleming, 2001). In this way, the production of radically new inventions is bounded by the search process to familiar parts of the knowledge space (Fleming, 2001).

The recombinant and cumulative characteristics of knowledge are stressed in the dynamics of the knowledge base. Using network analysis on patent classification co-occurrences, (Krafft et al., 2011) propose a further clarification of the concepts of exploration and exploitation (March, 1991) linking them to random and organised search. They propose knowledge property measures such as variety, coherence and cognitive distance to analyse knowledge evolution in biotechnology. In addition, they emphasise that random search is associated with the exploration phase in which technological variety and cognitive distance increases whereas knowledge coherence decreases. Subsequently, organised search implies that potential dominant variations can be selected, entering in the exploitation stage that results in a rise in coherence and a fall in cognitive distance and in the pivotal role of related variety.

The latter stream of literature places special emphasis on the process of recombination of different bits of knowledge. In this chapter we build on this literature, albeit focusing on variation as a potential solution to technological weaknesses. Therefore, the observations here are ex post recombined knowledge, instead of single pieces of knowledge. In doing so, we can assess the selection process, its trends and what knowledge has been selectively retained in technological evolution.

3.3 Measuring variation, selection and retention

3.3.1 Variation

In this section we describe the methodological framework that will allow us to investigate the properties of knowledge dynamics through the lens of evolutionary patterns. Our methodology concerns the exploration of the knowledge codified in patent data using citations among patents to build a knowledge network.

Patent data provide a great deal of information that can be exploited to analyse technological change. Patents are often used as a proxy for invention. In this outstanding number of studies, patent applications are used to analyse inventive activities and their diffusion (Lanjouw and Mody, 1996; Jaffe and Trajtenberg, 1999, 2002). In addition, many authors use technological classes, which specify the technological domains of each patent, to identify different properties of the knowledge base such as coherence (Nesta and Saviotti, 2005) and knowledge relatedness (Jaffe, 1986, 1989; Breschi et al., 2003).

Other studies use patent classifications co-occurrences to measure related and unrelated variety as well as coherence and cognitive distance (Krafft et al., 2011; Quatraro, 2010).

Different patent classifications are proposed by patent offices. In this work we use International Patent Classification (IPC) codes, established by the Strasbourg Agreement in 1971, through which technological specification is provided by means of hierarchical and language independent codes assigned to each patent.

As stressed before, we may think of patent classification codes as an underlying genetic structure. Therefore, from an aggregate perspective, each combination of IPC codes included in patents may represent an insight that a technological knowledge variety of the aggregate underlying structure has been proposed. When different IPC codes appear together in the knowledge space, we assume that a variation at the genotypic level occurs. Thus, we use the number of technological class combinations proposed each year as a proxy for variation.

3.3.2 Selection and retention

Another branch of the literature in innovation studies highlights the role of citations among patents to unfold technological advances and knowledge evolution (Mina et al., 2007; Verspagen, 2007; Fontana et al., 2009; Barberá-Tomás et al., 2011; Barberá-Tomás and Consoli, 2012; Epicoco, 2013; Martinelli, 2012). Indeed, citations can be employed to analyse various dimensions of technological knowledge developments synchronically and diachronically (Mina et al., 2007). Since the works of Garfield (1955); Garfield et al. (1964); de Solla Price (1965), and Hummon and Dereian (1989), citations have been extensively used to detect patterns of scientific knowledge.

The process through which citations are included in patents implies that the inventor and patent attorney place references to prior patents (and also other non-patent references) in the patent document that they are filing to the patent office. The list of references is controlled and, in some cases, filled in by the patent examiner that adds or deletes any missing or irrelevant citations to other patents (Popp, 2005). As a result, citations define the legal boundaries of the inventions limiting the scope of the patent property rights (OECD, 2009). Therefore, when patent A cites patent B, a technical relation exists between the two due to the knowledge included in previous patents (B) which more recent ones are built on (A).

In this work we assume that citations among patents can be used as a proxy for selection and that of all the variations that at any time are proposed to the selection environment, only a fraction are selected. Since citations are also good indicators of the quality and relevance of cited items (Popp, 2002), in this work patents that are cited are then selected.

To analyse 'what' is selected in the evolution of technological knowledge, we apply a method proposed by Hummon and Dereian (1989) for examining connectivity incitation networks. The authors developed three indices for identifying the main stream of knowledge within directed networks, i.e. the Main Path analysis (Hummon and Dereian, 1989; Hummon and Doreian, 1990). In order to define the importance of links and nodes in the network, the Search Path Count (SPC) algorithm (Batagelj, 1991, 2003) is implemented within Pajek, a software that enables the analysis of large networks[2]. After building a citation network in which each patent constitutes a node and citations among patents the arcs, we calculate the arc weights using the SPC algorithm. These weights are then used as a measure of importance of the single arcs on the whole network. Indeed, the algorithm builds on the idea that the more a source-sink path[3] passes through an arc, the greater the importance of that arc in the whole network (Batagelj et al., 2014)[4].

At this point a further clarification is needed to extend the theoretical framework described above. In order to identify the technological knowledge that is selected and retained in the citation network, we propose an index of knowledge retention ($IoKR$) that calculates the share of IPC codes that are passed on from the cited to the citing patent. The $IoKR$ is calculated as follows:

$$IoKR_j = \frac{s_{i,j}}{s_i}$$

where i is the cited patent and j the citing patent, whereas s_i represents the number of IPC codes assigned to the cited patents and $s_{i,j}$ the number of IPC codes that are present in both the cited and the citing patents. Therefore, when all IPC codes of the previous patents are also assigned to the following citing patents, the $IoKR$ equals 1 and 0 otherwise.

[2]http://vlado.fmf.uni-lj.si/pub/networks/pajek/

[3]The source-sink path comprises the nodes and arcs that connect each start point to any end point. A single node is both a start point and an end point.

[4]See Batagelj (1991, 2003); Batagelj et al. (2014) for the technicalities of this method.

The usefulness of this measure in the analysis conducted in this chapter is twofold. On the one hand, as stated before, some patents may inherit a part of the whole set of IPC codes and some patents may not share any of the IPC codes present in cited patents. This issue can be explained by the purpose of citations that may be assigned to define prior art which new patents build on, to indicate the state of art that preceded the patent and/or to emphasise the lack of novelty of the citing patent. Therefore, this measure can be used to analyse the selection process focusing on the technological knowledge that is selectively retained among variations, excluding those links that do not imply an inheritance of technological knowledge but may simply define the previous state of the art. For example, assuming an $IoKR$ of 1 we can calculate the number of times a combination of IPC codes is retained by following patents, whereas using a value >0 and <1, we can assess different degrees of retention of the underlying technological knowledge structure. In this way we discern between selection of just a part of the technological knowledge included in cited patents and selection of the whole technological knowledge in a specific variety.

On the other hand, we can combine the $IoKR$ with the main path analysis proposed before. This exercise allows us to find more coherent connected sub-networks of nodes in which knowledge retention is higher. Instead of using the SPC method to weight the arcs, we implement this measure to analyse the most retained part of the network.

3.4 Case study and the dataset

3.4.1 Electric and hybrid technological trajectories

The analysis proposed in this chapter focuses on the evolution of electric and hybrid vehicles, a technological trajectory that represents an alternative to the dominant internal combustion engine design.

The automotive industry is characterised by a 'routinised regime' in which the dominance of a few established firms is fostered by high appropriability and accumulation of technological knowledge that boost technological advantage over entrants (Malerba and Orsenigo, 1995, 1997). The industry has been challenged by significant changes in the selection environment over time. These mutations has been mainly driven by an increasing awareness of the environmental impact of vehicles. On the one hand, an increasing demand for low-emitting vehicles, and therefore a change in consumers' preferences, has shaped the technological knowledge dynamics of the whole industry, impacting technological competition (Oltra and Saint Jean, 2009a). On the other, environmental and innovation policies have provided the regulatory stimuli for enhancing the environmental performance of fleets.

The results of this changing environment have led to the development of alternative vehicles such as electric, hybrid and fuel cell propulsion systems, but also to the greening of conventional gasoline and diesel vehicles. However, at the current stage of development, none of these alternatives is ready to challenge the dominance of the internal combustion engine, at least with regard to economic and environmental performance (Frenken et al., 2004; Oltra and Saint Jean, 2009b).

In particular, the first electric vehicles were developed at the end of the 19th century during the onset of the automobile market where no-technology dominated. At the time, even if competition was between electric, gasoline and steam vehicles (Basalla, 1988), a few decades later, the gasoline car became the dominant technology and faces a period of consolidation from 1920-1973.

The dominance of the gasoline car was finally challenged during the '70s and '80s, when local air pollution, traffic congestion in large cities, car accidents and oil crises in 1973-74 spurred renewed interest in the electric car concept through the promotion of electric and hybrid vehicles programmes in the US, France and Japan as well as in many other countries (Cowan and Hultén, 1996). Despite the rather optimistic goals of these policies, they were ineffective in promoting electric and hybrid cars that remained uncompetitive when compared with gasoline vehicles. In 1990 California legislated the Zero-Emission Vehicle mandate in which automotive manufactures were required to provide emission-free vehicles for an increasing part of their fleet produced for sales, i.e. 2% in 1998; 5% in 2001 and 10% in 2003 (Sperling and Gordon, 2009). To this end, several start-ups and incumbent firms presented their EV as a response to this regulation. Even if California reached 4% and 12% of the world and US car market (Kemp, 2005), none of them exceeded 1500 manufactured units (Bergek et al., 2013).

Therefore, electric and hybrid vehicle technologies are of special interest in our analysis of technological evolution. In this respect, we are going to examine what happened in those years in which the selection environment moved toward environmental concerns on the impact of vehicle emissions. In addition, from an innovation perspective, these vehicles are involved in the development of technological knowledge that comes from different fields, such as chemical, electric and mechanical engineering, that highlight the complexity of the technological space.

3.4.2 Data

We collected patent data on electric and hybrid vehicle technologies using the technological subclasses reported in Appendix C[5]. We first downloaded the patents from the 'Thomson

[5]The IPC codes used in this study are almost the same as those used in Aghion et al. (2012) with some variations. We selected these IPC codes by reading their

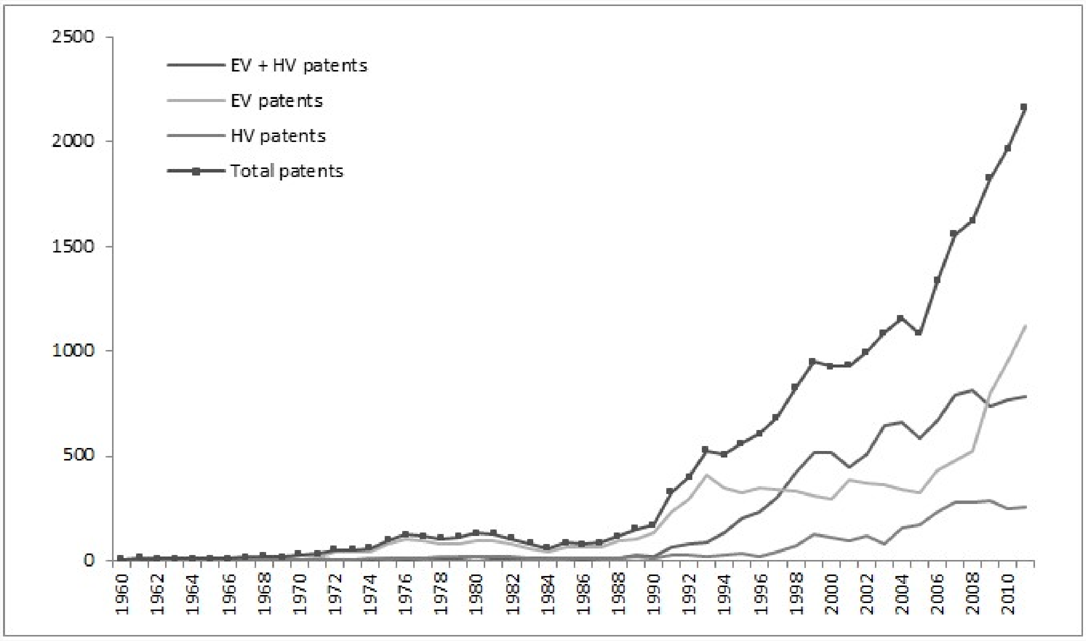
Innovation Database' and then collected all the cited patents of this former dataset. In this new set of cited patents we checked whether they were labelled with the IPC codes used in the first search and we excluded the ones that did not refer to any of these technological classes. The resulting dataset comprised 24,277 patents from 1901 to 2011.

With a focus on the period 1960-2011, Figure 3.1 shows the main trends in patenting activities. A first wave of increasing patent activities characterises the first years of the '70s. As pointed out before, in this period the renaissance of interest in electric cars stimulated technological advances largely driven by inventions related to electric vehicles (EVs) (light-grey line). However, the main rise in patent count is observed from 1990 onwards, when the California ZEV mandate was legislated.

Moreover, distinguishing between the technological domain of patents, we can see that after a first upsurge in EV patents, the technology faced a decline in the number of patents filed. This issue is related to the difficulties that inventors face in overcoming the hurdles that has penalized market penetration of electric propelled vehicles, i.e. high cost and performance limitations (travel range, speed and charging time). From 1997 with the introduction of the first hybrid-electric vehicle, the Toyota Prius I, more critical discontinuity occurred and hybrid vehicle patents started to rise. However, we should stress that the distinction between patents related to these two technologies is somehow blurred by the overlapping technological space in which electric and hybrid technologies develop. Hybrid vehicles combine an internal combustion engine with an electric motor and technological advances are focused on new components such as battery, electric motor, typically electric vehicle-related innovation, as well as on the integration of these components into conventional vehicle design.

description and checking the technological contents they refer to. In addition, we limited the search to those patents that present the words 'electric vehicle' or 'hybrid vehicle' in the title or abstract using wildcard characters.

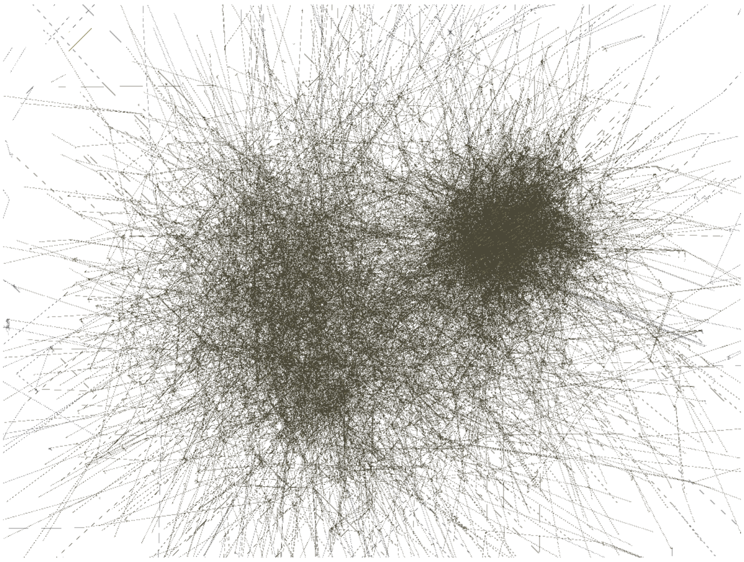
Figure 3.1: Total and technology specific patent counts in electric and hybrid vehicles (1960 – 2011)



Source: Own elaboration

Finally, we collected all the patents that cited the ones obtained through the first patent search. Following Martinelli and Nomaler (2014), the citation database contains only 'internal' citations, i.e., it includes citations to patents present in the starting sample (24,277) and excludes patents that are not cited or do not cite any other patent (single nodes). The resulting network, shown in Figure 3.2, is a directed acyclical graph consisting of 15,799 nodes and 23,315 arcs among the nodes.

Figure 3.2: Citation network



Source: Own elaboration

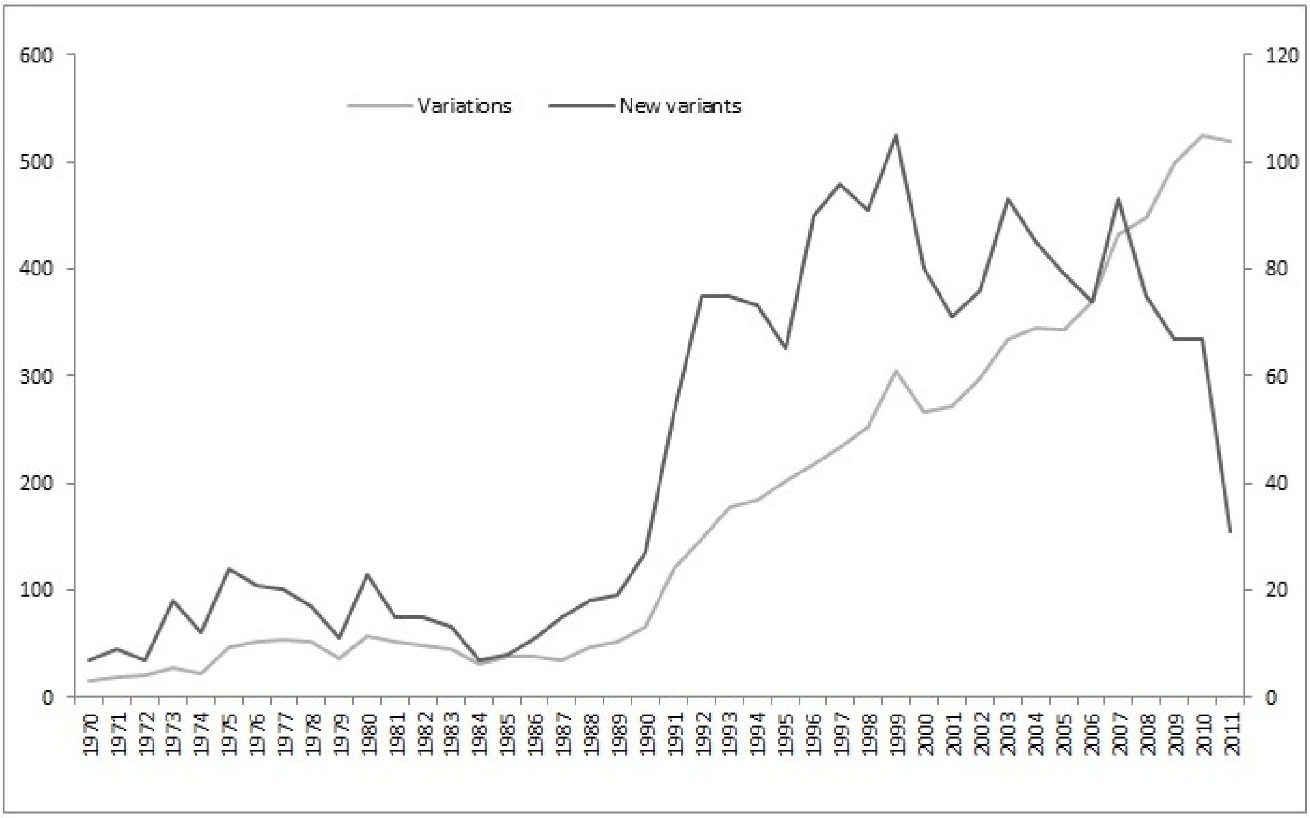
3.5 Empirical results

3.5.1 Variation and selection patterns

In order to derive insights into knowledge dynamics, we explore the patterns of variation and selection within the electric and hybrid technological space. As stated above, these technologies have faced growing concern, at least from a regulatory perspective, in two main periods, during the '70s and from the '90s onwards. This increasing interest has encouraged technological communities to develop potential solutions to the technological weaknesses that these technologies have experienced. Figure 3.3 emphasises this feature through the number of variations that are proposed to the selection environment by technological developers. In this case, we consider variations as the different combinations of 8-digit IPC codes that are disclosed each year. It should be noted that this count, as well as the others reported in Figure 3.3 and Figure 3.4, does not refer to how many patents with a specific

IPC code combination are filed each year, but on the contrary, it equally weights each combination. This allows us to concentrate this part of the analysis on the underlying dynamics of technological knowledge variation instead of focusing on how much a specific combination has been recognised as a promising technological domain to further develop, an issue that will be examined in the rest of the chapter. However, in order to obtain clearer, more reliable results, we include only those combinations of IPC codes that have been assigned to at least two patents over the period 1900-2011 in the analysis.

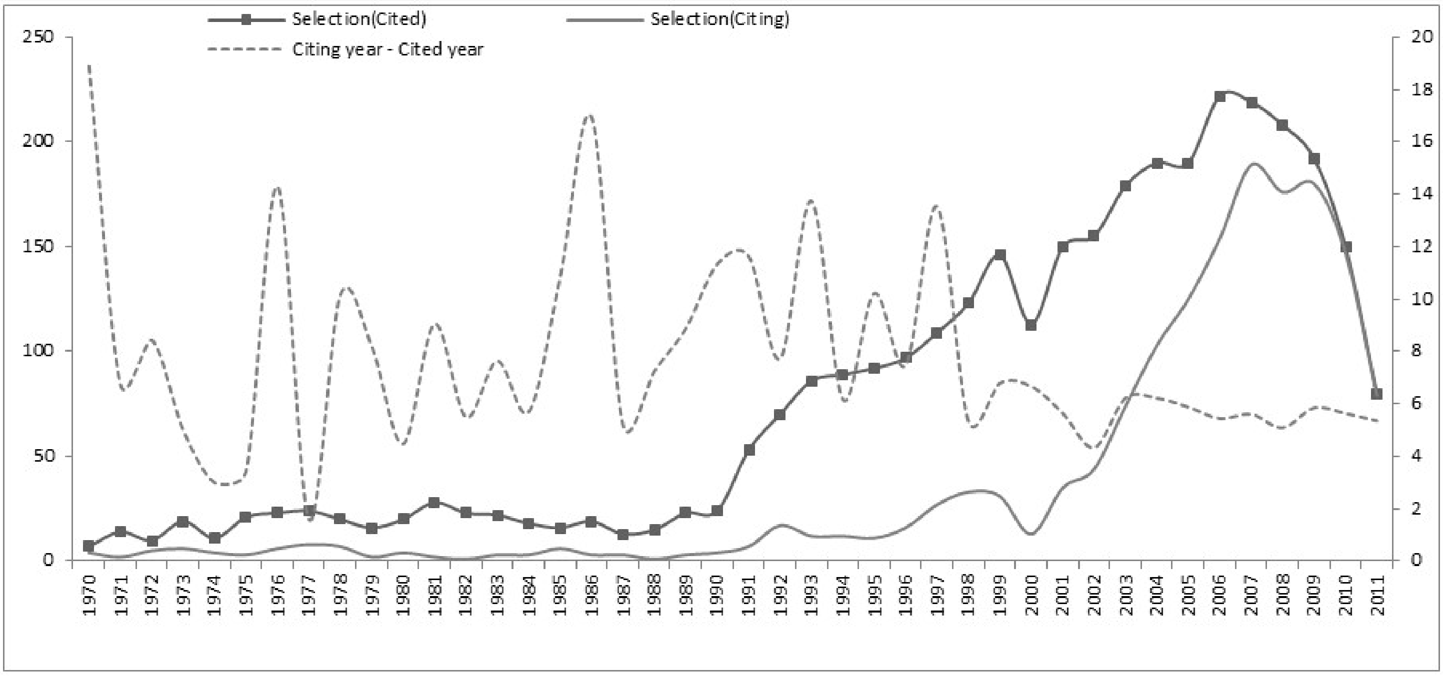
Figure 3.3: Variation pattern in electric and hybrid vehicles



Source: Own elaboration

After small and steady changes that characterised the evolution of EV and HV from the beginning of the 20th century to

Figure 3.4: Trends in selection in electric and hybrid vehicles



Source: Own elaboration

the 1970s[6], the number of variations slightly increased at the beginning of the '70s (Figure 3.3). This trend is then followed by a decline during the '80s and experiences a sharp rise after 1990. With regard to this point, we highlight the effectiveness of the ZEV mandate in triggering technological development related to these technologies, as can be seen from the increase in the number of variations during 1990-1999. However, a few years later when the mandate was relaxed in 1996, abolishing the 1998-2002 requirements and leaving in place 10% by 2003, the count undergoes a rapid decrease in 1999, regaining its momentum from 2002 onwards. This second rise in variations is associated with a period of discontinuity that occurred with the introduction of HVs onto the market. From 1997-1998, the year when the Toyota Prius I was launched, many inventors

[6]For the sake of comprehension, these values are not reported in Figure 3.3

began to improve HVs technologies as reported in Figure 3.1.

Nevertheless, even if the number of variations increased almost steadily from 1990 onwards, the introduction of new variations that have been never scrutinized before, followed a different trend, i.e. sharply growing from 1990 to 1992, slightly increasing from 1995 to 1999 (when it reaches the maximum) and gradually decreasing from then on. This represents an insight into how the exploration of new technological solutions increased as a consequence of the changing environment in which EVs and HVs evolved, and decreased with time. In addition, the difference in the number of variations and new variation trends underlines the fact that technological advances are increasingly directed towards specific technological domains, that is, the technological space, as well as the underlying knowledge structure related to electric and hybrid vehicles, are shaped and begin to characterise further developments.

Nonetheless, to obtain a clearer view of the patterns that distinguish knowledge dynamics, we derive another insight that shows whether the evolving knowledge structure exploits the variations proposed in previous years. In the analogy with biological evolution, we assumed that selection occurs when patents cite previous knowledge, building on the fact that when previous patents are cited their technological knowledge represents a knowledge source for citing ones. Using citations we face an additional problem related to the time lag between cited and citing patents. In this regard, Figure 3.4 accomplishes the task showing both the number of variations that are selected by forward variations (Selection (Citied)) and the number of variations that select previously introduced ones (Selection (Citing)). Focusing on the citing variations, we can observe that after the introduction of the ZEV mandate, the number of variations that select (cite) previous ones gradually rises until 1999 and faces sharp growth from 2000-2007. During the same period, the creation of new variations (Figure 3.3) gradually declines, meaning that whereas the creation of new IPC combinations decreases, the selection of previous combinations increases. We interpret these results as evidence that the exploitation of previous variations is increasing. This is confirmed by the trend in the number of variations cited that goes up with some fluctuations from 1990 onwards.

Finally, Figure 3.4 shows that the average difference between citing and cited years fluctuates from the beginning of the '70s to the end of the '90s and levels off from 2000. It is interesting to observe that whereas during the '90s this average flutters from 6.2 to 13.7 years, at the beginning of the 2000s, it stabilised at around 5.4. This provides another insight that, while in the former period variations recombined knowledge bits from older variations, in the latter they selected more recent knowledge from this explorative phase.

In conclusion, we should point out that the values reported in the last 3-4 years in Figure 3.3 and Figure 3.4 should not be considered. The decreasing trends are mainly due to the time needed to develop new variations, exploit the more recent ones, and file and publish patent applications.

3.5.2 Understanding what has been selectively retained

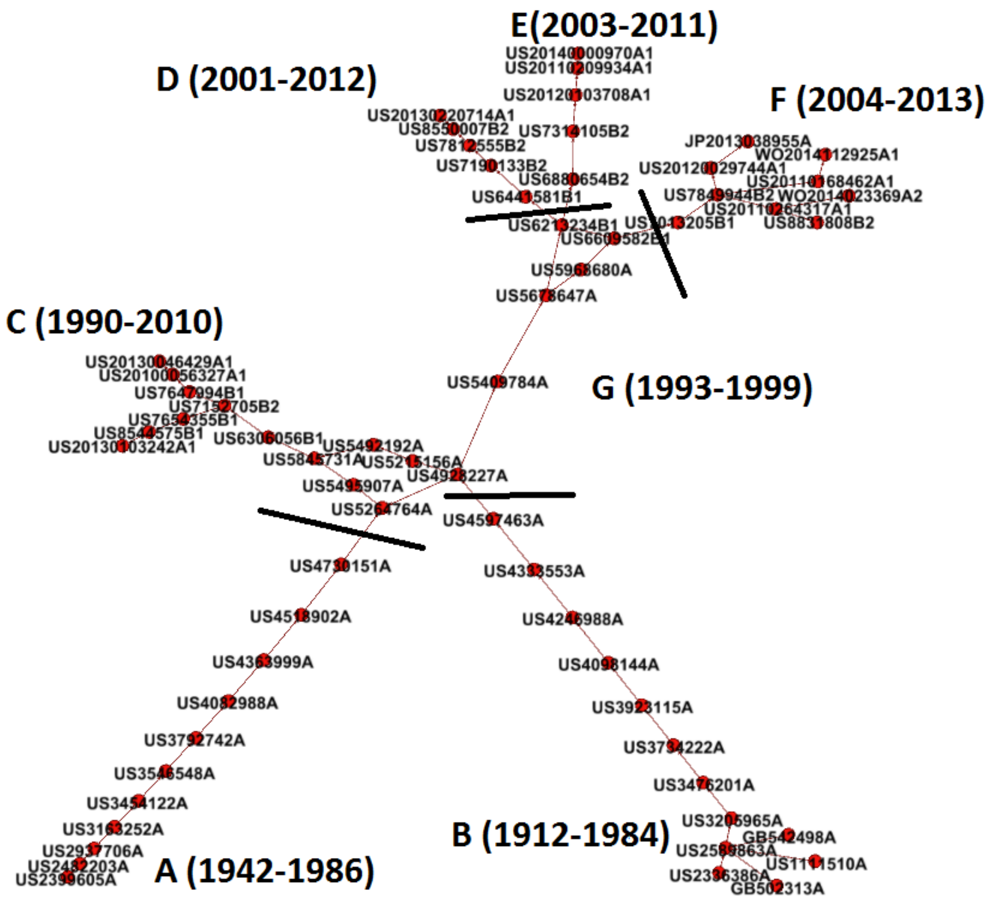
On the one hand, previous analysis helps us to identify the main trends in the development of electric and hybrid vehicle technologies, showing the patterns that characterise this evolution. On the other, from these results, another cornerstone of technological knowledge dynamics remains unsolved and refers to the investigation of 'what' has been selected and retained during technological evolution. Thus, we need to explore the complex architecture involved in these vehicles that integrate multiple technologies from different knowledge domains, such as electrical, chemical and electronic engineering.

To do so, in this section we explore the main steps taken by the technological community to solve technical problems using network analysis.

Figure 3.5 shows the source-sink path with the highest value. In this figure the arcs are equally weighted in order to obtain a clearer result of the technological advances over time. The older part of this sub-network is divided into two main streams of technological advances (A and B). The first trajectory (A) regards improvement and experimentation in the electric propulsion subsystem. This set of patents relates to electric motor improvements, regenerative energy systems (such as energy flow from braking) and control apparatus that regulate energy storage as well as the power supply from this energy storage unit and the propulsion system. The second trajectory (B) includes patents related to the integration of the electric motor into a conventional internal combustion engine vehicle and regenerative energy systems, such as regenerative braking. We can observe that since the 1970s, different attempts has been made to develop hybrid vehicles, on the one hand, through modification of the vehicle architecture integrating an electric motor and, on the other, through advances in regenerative energy systems to face the limited range of energy storage devices, a common problem in electric and hybrid vehicle designs.

These two main flows of technological advances converge at the end of the 1980s into two paths. The first set of patents (C) covers a time period of 20 years from 1990 to 2010. In this stream, technological advances are carried out to improve the integration of the electric motor and ICE. The hybrid concept pervades the whole trajectory, from the development of downhill regenerative systems and the introduction of the dual engine-hybrid motor to the creation of the series-parallel hybrid vehicle. This latter HV design, although more complicated and costly than other hybrid designs, is implemented in

Figure 3.5: CPM ignoring arc values



Source: Own elaboration

several modern HVs (Chan, 2002).

The second branch of patents included in (G) emphasises the attempt to achieve zero-emission vehicles through the development of fuel cell vehicles that are similar to series-type hybrids since the power generated by the fuel cell can be stored in the energy unit or directly supplied to propel the vehicle (Chan, 2007).

In addition, from the year 2000, this trajectory has given rise to three different paths. The first, D, is related to energy management systems able to improve energy efficiency.

Indeed, the energy flow from the energy refuelling unit to the electric motor and, in the opposite direction, from the regenerative unit to the energy storage device, needs to be properly controlled and optimised to reduce energy waste. The second route (E) undertaken by technological advances, concerns body design since the development of electric and hybrid vehicles follows two main directions: the conversion of existing conventional vehicles, i.e. replacement of the internal combustion engine with an electric motor without modifying the conventional body design of the automobile; and purpose-built vehicles (Chan, 2002).

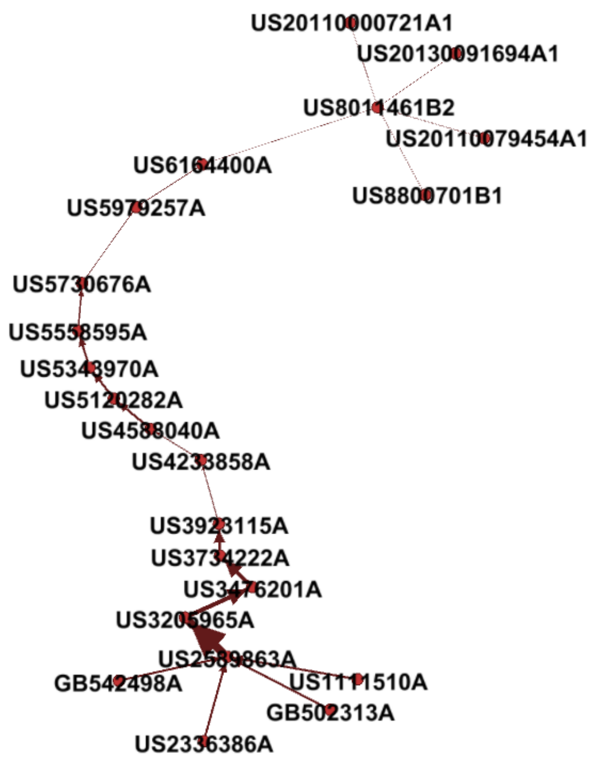
Finally, the third trajectory involves patents that enhance system optimisation such as driving supports and methods for controlling the charge state of the batteries.

As we can see, technological evolution has been characterised by the parallel development of two technical solutions, on the one hand, an electric vehicle, that involves the use of an electric motor and on the other, a hybrid vehicle that uses an electric motor and combines it with a conventional internal combustion engine.

The development of electric and hybrid vehicles has mainly regarded propulsion and energy source subsystems. However, in order to investigate what has been selected in the evolution of these technologies, Figure 3.6 shows the CMP trajectory using SPC values. This sub-network is the path with the highest total sum of weights calculated using the SPC method. It captures the main directions of technological knowledge creation from the 1930s to 2011.

The most important part of the whole network emphasises hybrid propulsion as a short-term solution to facing the environmental impact of conventional vehicles. The nodes at the bottom of Figure 3.6 concern technological advances in the design of electric vehicles and electric motors. Indeed, as in the previous case, the technological knowledge produced be-

Figure 3.6: CPM using SPC values

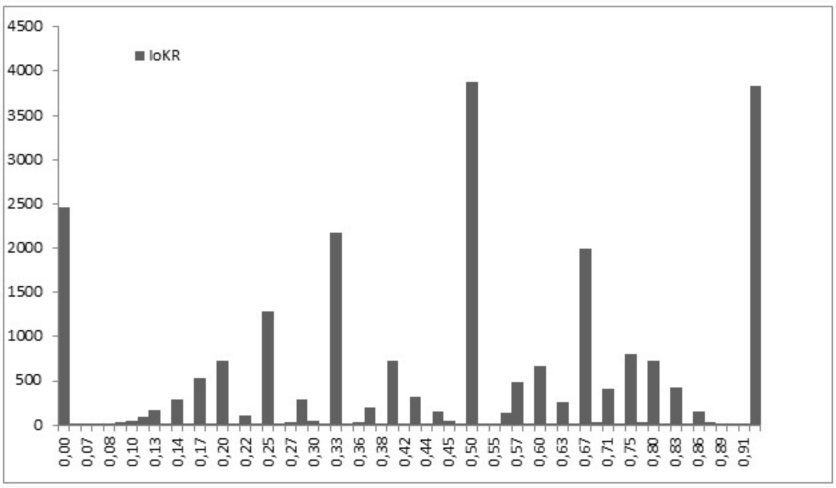


Source: Own elaboration

fore 1970 concerns improvements in electric motor devices. In the middle of the path (from the 1970s), hybrid technology emerges from progress in the transmission systems and devices that characterised the '90s. Finally, it concludes with control system advances that, as discussed before, represent a challenge to improving vehicle performance. From these results, it is interesting to highlight that whereas at the beginning of this trajectory the focus is on development of the propulsion subsystem and in particular the propulsion unit, as we proceed along this path, we observe that technological advances gradually shift from mechanical components to electrical components.

Finally, in the last exercise we identify the technological knowledge retention that underlies the dynamics of technical advances. To this end, Figure 3.7 shows the distribution of arcs with respect to the $IoKR$ presented before. As we can see, two values are particularly frequent, i.e. 0.5 and 1. This means that many arcs (almost 30%) that form the whole network involve the inheritance of half of or the total number of IPC codes included in the cited patent. Thus, we use these thresholds to cut the network and analyse through the CPM the source-sink path with the highest total sum of the values obtained through the $IoKR$. This exercise differs from the previous one in the way arcs weights are calculated. In Figure 3.5 and Figure 3.6 the arc values are calculated using SPC methods, identifying how many times the path from each start point to each endpoint passes through the arc, whereas here the focus is on the rate of retention of IPC codes in following patents.

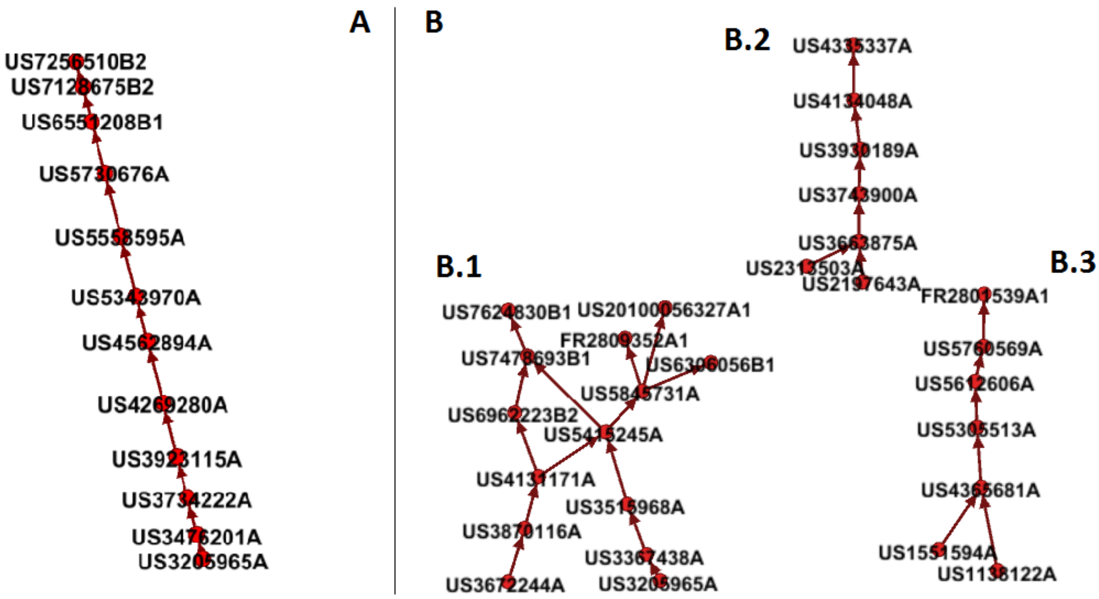
Figure 3.7: 8-digit IoKR distribution



Source: Own elaboration

Figure 3.8 shows the two sub-networks, the first (A) using lines with values greater than 0.5 and the second (B) with values equal to 1 (implying that the whole set of IPC codes is passed from cited patents to following citing patents). Trajectory A mainly regards the development of hybrid vehicles. It begins in the 1960s and, until the 1990s, the focus is on the propulsion subsystem and concentrates on coupling of the electric motor and internal combustion engine. From the 1990s, technological advances still regard the propulsion subsystem but with a specific focus on mechanical transmission instead of the power unit, focusing mainly on the integration of parallel transmissions capable of receiving input power from more than one source (e.g. electric motor and internal combustion engine). This is fundamental for the development of parallel, series-parallel and new hybrid vehicles with planetary gear units.

Figure 3.8: CPM in the network with arcs values greater than 0.49 (A) and equal to 1 (B)



Source: Own elaboration

By cutting the whole network and assuming complete inheritance of cited patents inheritance (B), three main sub-network are detected[7]. The first trajectory (B.1) regards technological advances in mechanical components related to the propulsion system such as flywheels, dual engine propulsion, etc., and their integration in the vehicle architecture. The second sub-network (B.2) focuses on current or speed control systems of the electric motor improving its performance. Finally, in B.3 we can find patents related to the energy source subsystem, in this case, the batteries and their configuration in the vehicle architecture.

These last results emphasise the domain in which technological knowledge has a high retention rate. These are the components that provide high inheritance of previous knowledge that is recombined with other bits of knowledge to provide solutions to those technical weaknesses that limit the potential substitution of ICEVs with EVs and HVs.

3.6 Conclusions

In this chapter we analyse the patterns of variation, selection and retention that characterise technological knowledge evolution. We propose an analogy between the evolution of biological organisms and technological knowledge using patent data and technological classes to identify individuals within a specific species and their genotypic level. The focus is on the alternative technological trajectory that involves technological advances in electric and hybrid vehicle technologies, considered in this analysis as species in which the underlying genotypic structure grows.

Several efforts are pursued to make electric and hybrid vehicles affordable. In particular, policy regulations have been particularly effective in triggering the development of these

[7] All the sub-networks have a total sum of weight equal to six and, for this reason, the CPM finds three sub-networks.

technologies. Indeed, the California Zero-Emission Vehicle mandate in 1990 has induced technological progress regarding alternative vehicles and electric and hybrid cars in particular.

Our findings suggest that in the years that followed the introduction of legislation, the number of IPC code combinations (used as a proxy for variation) increased highlighting that an explorative phase had begun. Subsequently, although the number of new variations stabilised, the selection of these variations increased. This may be interpreted as the beginning of an exploitation phase in which the variations presented to the selection environment were selected.

Finally, in our analysis of what has been selected and retained, the results highlight that at the beginning of the last century, many efforts were made to improve the performance of the electric motor. In the same period, hybrid vehicles emerged from integration of an electric motor with conventional vehicle design. The results underline that whereas at the beginning of the century technological advances in mechanical components characterised the development of these technologies, in recent years, a gradual shift to electric and electronic components has been experienced. Indeed, advances in vehicle system optimisation and the implementation of energy management systems have been particularly important in the evolution of these technologies.

Chapter 4

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

Abstract:This chapter aims to shed light on the drivers that encourage a shift from incumbent internal combustion engine technologies towards low-emission vehicle technologies. We emphasise the role of fuel prices, one of the main drivers of environmental innovation, and other features of the technology space (such as technological proximity), in impacting technological dynamics and fossil fuel technological lock-ins. Specifically, we investigate whether green technological efforts come at the expense of other environmental or non-environmental inventive activities. In doing so, we employ Self-Organised Maps (SOMs) to detect the main technological domains exploited by the automotive industry during the period 1982-2008, using triadic patent families as a proxy for technological efforts pursued in each technological field. On the one hand, we test whether these drivers foster the substitution of non-green patents with green ones. On the other, we analyse if they favour substitution between technological efforts related to alternative vehicles, de facto influencing low-emitting vehicle competition. Our findings suggest that higher tax-inclusive fuel prices (used as a proxy for carbon tax) are effective in redirecting patenting activities from non-green to green technological fields. In addition, we observe a similar impact when we focus on green technological fields. Although this result may involve the risk of potential lock-in into sub-optimal substituting technologies, there are insights that the competition within the environmental technological domain mainly regards technological efforts spent on greening conventional cars and developing low-emission vehicles.

4.1 Introduction

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

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

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

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

In this complex framework where uncertainty, path - dependence and competition (ICEVs vs. LEVs and between LEVs) stand out, several authors highlight that policy intervention may represent one of the main factors that will allow sociotechnical lock-ins to be overcome (Faber and Frenken, 2009;

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

Rennings et al., 2013), and specifically, ICEV lock-in to be avoided (Cowan and Hultén, 1996)[2]. During recent decades, many authors have highlighted the role of environmental policies in inducing the development of environmentally-sound technologies (Popp et al., 2010; Bergek and Berggren, 2014). However, when technologies compete, even if it has been emphasised that environmental policies lead to increasing innovative performances and market competitiveness (Porter and Van der Linde, 1995), the production of eco-innovation sometimes causes secondary effects; these include environmental rebound, green paradox and crowding-out (van den Bergh, 2013).

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

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

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

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

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

The chapter is structured as follows: Section 4.2 introduces the related literature and Section 4.3 explores the main features that characterise the automotive technological system presenting the data and identifying the main technological trajectories through Self-Organising Maps (SOMs). Section 4.4 describes how we build our main variables and the empirical model whereas Section 4.5 discusses the results. Finally, Section 4.6 concludes.

4.2 Literature review

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

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

In order to understand the overall effect of green regulation on the economic system, we study its potential, secondary consequences, i.e., the potential crowding out effect, that eco-innovation may have on other innovation, should be investigated to appreciate the overall impact beyond the development of new green technological efforts.

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

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

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

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

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

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

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

Mainly due to the research questions they answer, these studies focus on the environmental innovation effect without directly examining the role of environmental policies. An exception is Hottenrott and Rexhauser (2013) that employs survey - based data in order to detect which firms introduce environmental technologies as a consequence of policy compliance behaviour. The study suggests that while there is evidence that environmental innovation crowds out firms' in-house R&D expenditure, this does not seem to influence the number of existing R&D projects, their outcome or the amount of investments in fixed assets (both innovation-related and others). In addition, the authors advocate that firms prefer scaling down long-term oriented R&D activities that are not directly connected to production and that provide relatively uncertain returns.

Our work takes advantage of the findings of these studies to analyse whether environmental policy stringency encourages a shift from non-environmental inventions to environmental ones. In doing so, we fill the gap in the literature that assesses

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

the effectiveness of environmental policy in unlocking the technological system from path dependence on non-environmental inventive efforts. Therefore, the first research question is the following:

RQ1. Does environmental policy induce a shift from non-environmental invention to environmentally friendly inventive activities?

Finally, two main propositions are put forward from the literature on technological substitution (David, 1985; Arthur, 1989). First, even if substituting technologies are available and superior to the dominant one, technological substitution is not assured due to the presence of increasing returns to adoption. Second, in a technological substitution process, a pool of new technologies compete for dominance although lock-ins into sub-optimal substituting technologies are still possible due to path dependence of sequential adoption decision. With regard to these points, in the automotive industry both propositions apply, at least in part, due to the presence of competition between conventional and low-emitting vehicles and between alternative vehicles designs that may substitute conventional cars (Frenken et al., 2004).

Due to the fact that the potential shift from non-green to green inventions may also affect the environmental domain because of competition between low-emitting vehicle technologies, i.e. green inventions come at the expense of other green inventions, we investigate 'what' has been crowded out. In this case, if environmental policies drag away resources from environmental technological domains to develop other green inventions, the risk of technological change lock-ins into a sub-optimal substituting technology will be higher because of the absence of a superior alternative technology, from both an economic and environmental perspective, at the current stage.

This leads to the second research question:

RQ2. Does environmental policy alter competition between alternative low-emissions vehicles? Does it cause a shift among environmental inventive activities?

4.3 The automotive technological system

4.3.1 Patent data in the automotive sector

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

(Laperche et al., 2011).

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

In this chapter, we employ a methodology based on triadic patent families defined by the OECD as a 'set of patents taken at the EPO, USTPO and JPO that share one or more properties' (Dernis and Khan, 2004, p.17). One of those properties is that patents must pertain to the same patent family[5]. In doing this, we focus on high quality patent data since most important inventions are protected in these three patent offices. Moreover, we reduce the influence of the heterogeneity of patent offices' regulation systems (Dernis and Khan, 2004). In addition, to deal with patent sample selection problems that come from the type of search that is carried out[6], we collected the automotive firms included in the R&D scoreboards (IRI) from the 2006-2011 editions[7]. In doing so, we focus on firms that perform constant and considerable amounts of R&D investment. Indeed, incumbent firms are expected to carry out

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

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

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

large R&D programmes thanks to consolidated financial and R&D capabilities (Cohen and Klepper, 1996). Subsequently, we gathered the patents filed by those 71 firms, retrieving their name from the Derwent Corporate Tree[8] in order to obtain the whole corporate structure and their standardised applicant names. This process allows us to account for the complex globalised structure of the automotive industry and reduce noise caused mainly by spelling variations in assignees' names.

4.3.2 Self-Organising Maps

We collected all the patent family applications filed by the former sample of firms from the Thomson Innovation database obtaining a total of 247,510 patent families, of which 54,371 are triadic patent families (TPFs). In addition, we discerned between green and non-green TPFs by exploring their technological classification codes. Different technological classification have been proposed to analyse the technological content of patent data. In this chapter we use Cooperative Patent Classifications (CPC) codes[9] , which provide a hierarchical and language independent classification of patent technical domains. In particular, what makes this classification appealing for our study is the possibility of detecting green patents through the Y02 class "Technologies or applications for mitigation or adaptation against climate change" that we use to identify the environmental inventions in our dataset.

Figure 4.1 illustrates the trends in green and non-green TPF applications sorted by their earliest priority year. We can appreciate from the histograms that the percentage of

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

[9]CPC is a new classification introduced in the USPTO and EPO that includes a section for emerging technologies (http://www.cooperativepatentclassification.org). For an application of CPC patent maps, see (Leydesdorff et al., 2015)

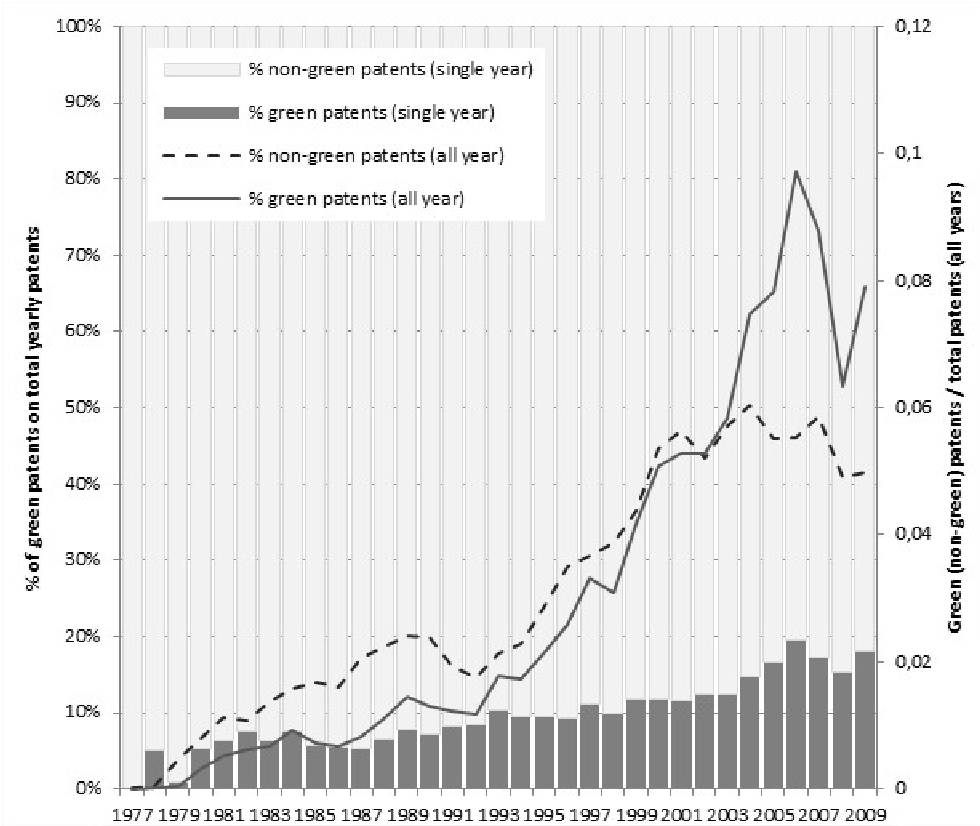
green TPF per year steadily rose from 1980 to 2006 (when it reached its maximum) and then gradually fell until 2009, whereas the percentage of non-green patents followed the opposite trend. Moreover, we can appreciate that the percentage of green and non-green TPFs over the total (respectively, green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

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

Thus, we created a distance-based patent map using a Self-Organising Map (SOM) mapping technique (Kohonen, 1990, 2001). The SOM is a unsupervised neural network that represents multidimensional data in a two-dimensional space which

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

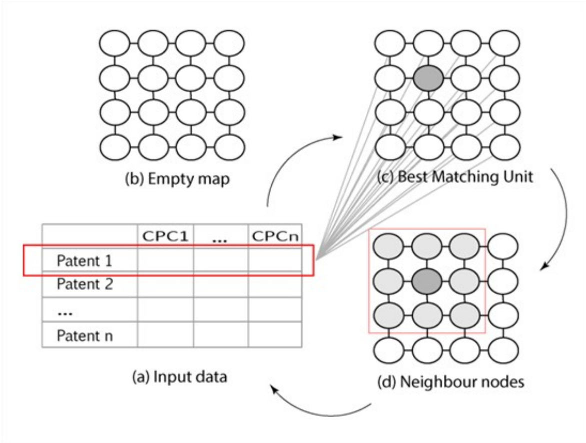
Figure 4.1: Green and non-green patent trends and percentage of green patents over total yearly patents



Source: Own elaboration

returns the similarity between input data. The process is based on a map of interconnected nodes to which the input items are assigned according to the Euclidean distance (ED) between nodes' weight vectors and input vectors. Figure 4.2 (a) shows how input data have been introduced in the present exercise, i.e. each row represents a patent, the columns denote CPC codes and matrix values indicate whether a CPC is assigned to the patent (1) or not (0). Since the technicalities of this methodology are described in detail elsewhere (Kohonen, 1990, 2001, 2013; Vesanto, 1999) (as well as in Appendix B), we will briefly describe the output of this process.

Figure 4.2: Steps of SOM algorithm



Source: Own elaboration

After the initialisation step, where the weights are assigned to the empty map (Figure 4.2 b), a batch algorithm (Kohonen, 2013) is implemented. In each step, the SOM randomly selects an input (in our case a patent) and detects the map node with the lowest ED (Best Matching Unit - BMU) between it and the initialised nodes of the maps (Figure 4.2 c). This step is iterated until each input is assigned to a map node. Subsequently, a radius defines the neighbours for each BMU, i.e. a set of nodes close to the BMU (Figure 4.2 d). Finally, the neighbour node weights are modified to become more similar to the BMU, and pushed closer to the BMU. This feature allows the map to represent the similarity between the input data, decreasing the distance between similar map units and, therefore, increasing the one between different units.

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

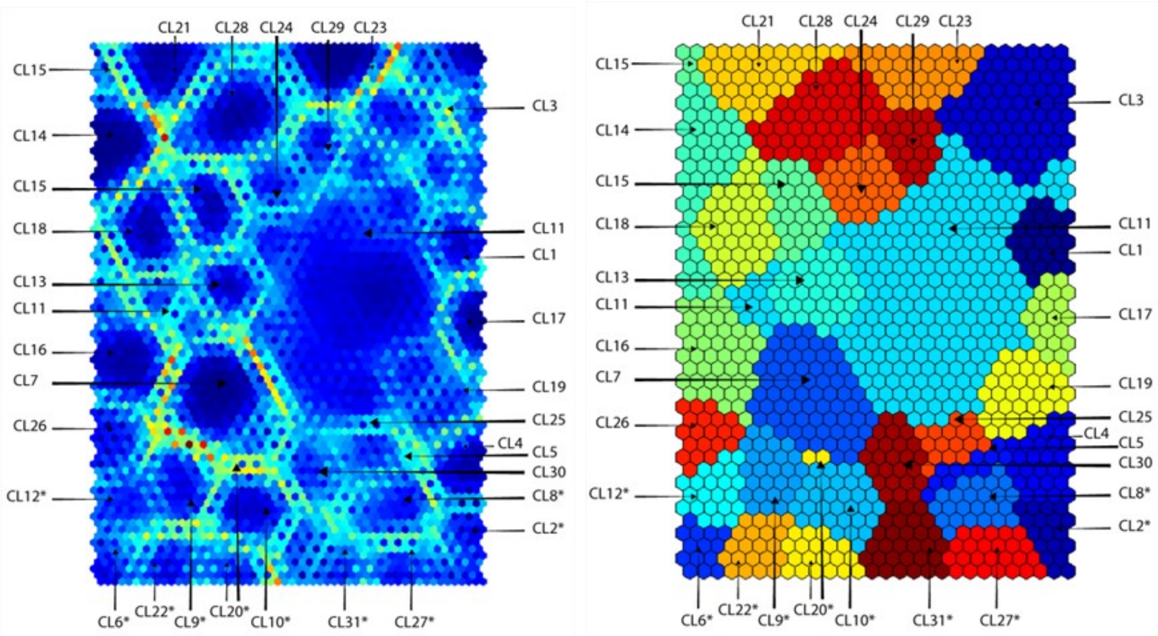
iii) measure the relatedness between these clusters. In comparison to other techniques and methodologies to retrieve the cognitive distance between technological fields, the SOM provides a distance-based output where the patents are located according to their global and local similarity.

4.3.3 Exploring the technological space

In order to define the technological clusters, we applied the non-hierarchical k-means clustering technique (MacQueen et al., 1967) on the SOM output, obtaining 31 clusters[11]. The SOM and k-means algorithm outputs are illustrated in Figure 4.3. Figure 4.3 (left) shows the distance between nodes and their closest neighbours, i.e. the Unified-distance Matrix (UMAT), whereas Figure 4.3 (right) reports results of the k-means clustering process applied to the SOM.

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

Figure 4.3: Unified-distance matrix and clustering results



Source: Own elaboration

Table 4.1 lists the main keywords[12] associated with the 31 invention clusters that the combined procedure has detected. In addition, the right columns of the table provide the number of patents in each cluster and the percentage of green patents. It is noteworthy that the clustering exercise has correctly identified and placed green inventions creating clusters consisting almost entirely of environmental patents.

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

Table 4.1: Description of clusters.

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

As far as the location in the map is concerned, Figure 4.3

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

What is more, the rest and the majority of the technological space is characterised by non-green inventions. In the centre of the map, Cluster 11 appears to have the highest share of nodes compared with other clusters. This is confirmed by the fact that almost one third of the patents are included in it. This cluster contains heterogeneous components such as mechanical and electronic apparatus (e.g. air conditioning systems, automatic door opener, etc.) and car designs that are not directly related to the powertrain system. In addition, we can observe two main directions of technological advances that begin from the area closer to green technologies towards the upper side of the map. On the one hand, Cluster 4, 5, 25, 19, 17 and 1 contain patents related to engine mechanical components and catalytic converters. The former refers to technologies linked to the powertrain system, while the latter to systems that regard end-of-pipe technologies outside the realm of green technologies (e.g. silencers). On the other hand, the left part of the map is characterised first by inventions related to the battery system (Cluster 30 and 7) and other elements such as cruise assistance (Cluster 26) and control systems (Cluster 16). A separate discussion is necessary for Cluster 13, 14, 15, 21 and 24. Those clusters include mechanical developments in transmission (13-15), suspension (24) and brake systems (21).

Concluding our description of the technological space, we find safety technologies in Cluster (23) and tyres and pneumatics patents in Cluster (3).

4.4 Testing the crowding out hypotheses

4.4.1 Dependent variable

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

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

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

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

This is the difference between the growth rate in the patent count moving average in a green cluster (g) and the one related to a non-green cluster (ng). i represents each couple of green and non-green clusters. Therefore, when the CO variable is positive, the growth rate related to green clusters is higher than the one in a non-green cluster. We assume that positive values of this variable imply a shift in the technological advances toward more sustainable technologies.

Similarly, the CO variable can be used to test the potential crowding out effect among green clusters as follows:

$$CO_{i,t} = |\Delta PAT_{g1,t} - \Delta PAT_{g2,t}|$$

where CO is equal to the difference between two patent count moving averages related to $g1$ and $g2$ (with $g1 \neq g2$) with s representing each couple of green clusters. The absolute value helps us to interpret the results since the output in this case is bidirectional.

Therefore, we test the first and second research questions on a total of $g * ng * t$ and $g(g-1)xt$ observations respectively[13].

The strength of this approach resides in the capability to account for relative increase (decrease) in patent counts related to both technological clusters ($gvs.ng$ and $g1vs.g2$), i.e. a technological field increases more than in proportion to another.

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

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

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

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

4.4.2 Independent variables

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

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

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

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

where $EP_{c,t}$ is the tax-inclusive fuel price defined as the average between diesel and gasoline price (Figure 4.4).$w_{i,c}$ is a cluster-specific weight that captures the importance of country c in both green and non-green clusters. We therefore define for each cluster the weight of country c according to the origin of the assignees and to the number of their patents in the cluster. Therefore, the higher the percentage of patents filed by country c, the greater $w_{i,c}$. In order to avoid potential sources of endogeneity deriving from the correlation between patents and fuel prices (Popp, 2002), we calculate w as a time-invariant weight using data over the whole period 1986-2009. Moreover, due to the fact that the production of inventions in the automotive industry is mainly concentrated in three geographical areas, c corresponds to EU, JP and US[15]. Therefore, $EP_{c,t}$ includes the Japanese and American fuel price and the average fuel price between European countries.

Moreover, substitution between the two fields may be driven by the characteristics of the technological space. The $PROX$

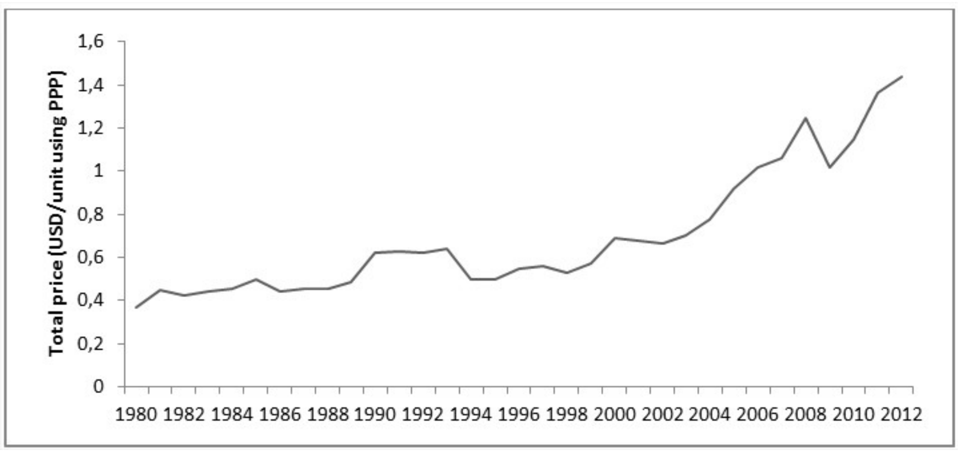
[14] Aghion et al. (2012) exploited the firm-level variation using the firm share of patents filed at country c.

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

variable is included to test the effect of relatedness between the technological fields. Indeed, in the new knowledge search process, firms (through routinised behaviour) search in the closest knowledge fields to reduce the uncertainty of the process (Boschma, 2005).

Nelson and Winter (1982) emphasises that what emerges when firms search for new knowledge is often uncertain and unexpected. Therefore, the research opportunities found within clusters at a lower cognitive distance may induce firms to consider those technological fields as potential sources of knowledge to lower uncertainty.

Figure 4.4: Average post-tax fuel price between premium unleaded 95 RON and diesel in OECD countries



Source: Own figure using data from IEA

Hence, competition between two clusters may be explained by their cognitive proximity in the sense that closer knowledge base may provide opportunities for further improvements in the technological field under investigation.

The literature provides different ways of measuring cognitive distance. Using a matrix and tracing R&D expenditure from the industry of origin to the industry of use of the resulting products and services, Scherer (1982) assumes that two industries can be considered close if there is a high share of R&D performed in one industry and used in the other.

Distinct from the user-producer-oriented methodology, the co-occurrence of classification codes within a patent document is employed to identify the relationship between the knowledge base in different fields. The assumption is that co-occurrence measures the strength of the knowledge link and spillovers between the technological areas.

Jaffe (1986) calculates the distribution of patents over 49 technological fields on a sample of US firms and measures the correlation (angular separation) between the research efforts performed in each innovative area, obtaining the similarity between firms' R&D activities through a cosine index.

Following Jaffe (1986), we calculate the distance between cluster centroids in the technological space defined above (Figure 4.3) and employ it as a proxy for knowledge relatedness between technological fields.

In order to exploit the cluster-pairwise variation of our dependent variable, we calculate the relatedness ($PROX$) between technological efforts as follows:

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

where technological proximity between each couple of clusters (i) is equal to the number of patents in the non-green cluster ($PAT_{ng,t}$) divided by the distance between the centroids of the two clusters ($DIST_i$). This formula allows us to weight the knowledge included in non-green clusters by its similarity to the green one. Therefore, higher distance between two clusters is associated to lower technological similarity (holding distance as constant).

Thus, firms may drive away inventive activities within low cognitive distances which implies that the search process is carried out among similar technological fields. For example, inventive efforts in new promising environmental technological fields may reduce other kinds of technologies that are related to the internal combustion engine (competing technology), rather than decreasing other elements of the powertrain system (i.e., transmissions) that may also be adopted in alternative vehicles.

4.4.3 Other variables

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

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

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

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

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

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

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

4.5 Results

In this section we present and provide an explanation for the results for both hypotheses tested over the period 1982-2008 (26 years), i.e. green vs. non-green and green vs. green inventive activities. Table 4.2 shows the descriptive statistics and Table 4.3 the correlation matrix for both the models.

Table 4.2: Descriptive statistics

Gr. vs. Non-Gr					
Variable	Obs	Mean	Std. Dev.	Min	Max
CO	5670	-2.233774	11.27849	-80.25	43
EP (t-1)	5670	1.037521	.4561879	.1190692	2.337916
PROX (t-1)	5670	71.1831	161.6976	0	2412.939
CIT (t-1)	5670	.9640212	4.023495	0	82
F (t-1)	5670	3.183774	2.92954	0	18
PS ng (t-1)	5670	287.1834	579.0677	0	4769.544
PS g (t-1)	5670	68.0297	83.43386	0	478.0059
Gr. vs. Gr					
Variable	Obs	Mean	Std. Dev.	Min	Max
CO	2430	2.834568	3.325596	0	24
EP (t-1)	2430	1.00259	.4640165	.1162741	2.200845
PROX (t-1)	2430	38.94946	87.48263	0	1050.328
CIT (t-1)	2430	2.453498	7.494261	0	98
F (t-1)	2430	2.394239	2.485058	0	12
PS g (t-1)	2430	68.0297	83.44367	0	478.0059

4.5.1 Green vs. non-green patents

As far as competition between green vs. non-green inventive activities is concerned, the results of the fixed effects linear model are shown in the first column of Table 4.4. Independent variables are lagged by one year in order to account for the

Table 4.3: Correlation matrix

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

time to exploit inventions[16], a common practice used in other related studies (Aghion et al., 2012; Lee et al., 2011; Popp and Newell, 2012).

When analysing the results, we observe that an increase in tax-inclusive fuel prices enhances the likelihood that green inventions come at the expense of non-green ones. Since environmental regulations trigger environmental automotive inventive efforts (Aghion et al., 2012; Lee et al., 2011; Hascic et al., 2009), the results seem to provide evidence that firms tend to reallocate R&D resources from non-green to green investments due to the need to comply with policy requirements. This result can be interpreted as an insight that post-tax fuel

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

prices impact competition between the two technological fields and contribute to crowding out ICEVs inventive activities in favour of alternatively propelled vehicle technologies. Therefore, on the one hand, we advocate that environmental regulation is effective in unlocking the automotive technological system from path dependence on conventional vehicle innovation. Higher fuel prices encourage firms to carry out environmental inventive activities while discouraging dirty invention development (Aghion et al., 2012). On the other hand, an increase in environmental policy stringency hampers non-environmental patent efforts and thus the social benefit that arises from new eco-innovation.

Other remarks can be extrapolated from the proximity variable. The coefficient indicates that the greater the dissimilarity between technological clusters (i.e. distant cluster in the technological space), the lower the shift from non-environmental to environmental inventive activities. Thus, we point out that firms have a tendency to reduce efforts in the technological clusters that are closer (i.e. related in terms of CPC classes) to the green ones. From Figure 4.3, we observe that more distant technological clusters (the upper side of the map) with respect to green clusters, are not directly related to internal combustion engines. This issue highlights the fact that, when holding constant other variables, firms' patent strategies are directed towards increasing efforts in environmental technologies at the expense of non-green inventions such as conventional engines, or alternatively, that this effect is lower for those clusters that are more distant in the technological space. This result confirms the abovementioned competition between the main technological trajectories in the automotive industry. The efforts made in these alternative powered engines (such as hybrid, electric and fuel cell), compete with inventions directly related to fossil fuel engines rather than with technologies that can also be adopted in alternative cars, i.e. safety, transmission, brake technologies and tyres.

4.5.2 Green vs. green patents

In addition, we investigate the potential effect of environmental policy on competition between green technologies. This issue is fundamental to testing whether green inventions drive away inventive efforts from other green fields due to policy stringency or other factors that influence technological competition. In so doing, we account for the effect of each green technological cluster on the others included in the green domain. From Table 4.4 column 2, we can observe that the environmental policy coefficient is positive and significant. This means that there are insights that tax-inclusive fuel prices impact competition between alternative technological advances. Therefore, this issue highlights that environmental policies may redirect technological efforts towards other environmental domains increasing the likelihood of a potential lock-in into sub-optimal alternative technology.

However, the technological neutrality of tax-inclusive fuel prices, instead of inducing improvements in a particular technological field, should encourage firms to exploit a variety of technological trajectories (Oltra and Saint Jean, 2009b) because, at the current stage of technological advances in low emission vehicles, it is hard to assess whether an alternative technology is superior to the others. For example, even though fuel cell vehicles are considered the most promising technology compared with hybrid and electric cars, important bottlenecks must be solved and therefore the risk of lock-in into a technology which may turn out to be sub-optimal in the future remains (Frenken et al., 2004).

Furthermore, we provide a suggestive interpretation of these results by categorising the clusters within four main groups. As stated before, the main trajectories that characterise green R&D efforts are end-of-pipe technologies, HVs, EVs and FCVs.

Following Popp and Newell (2012), Table 4.5 shows the correlation between the percentage of patents per year in each category among three time ranges. We can observe that the highest negative correlation is between end-of-pipe technologies and other vehicle propulsion technologies in all time ranges. This issue provides insights that competition between green patenting activities mainly regards these two broad categories of technological efforts i.e. end-of-pipe vs. EVs, HVs and FCVs. Thus, even within the environmental technological domain, the competition between the two vehicle designs characterises the technology space.

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

4.5.3 Robustness analysis

In this Section we provide some robustness checks to assess the reliability of the model results using different variables. Table 4.6 shows the results employing a 3, 4, 5 year patent count moving average as dependent variable. Previously, a 4-year moving average was used to provide the main results, although we can observe that coefficient signs and their significance are almost the same using different dependent variables in both models, at least as far as the main independent variables are concerned.

Moreover, we run the model using a different proxy for the environmental policy variable (Table 4.7). Whereas results in Table 4.4 are obtained using tax-inclusive fuel prices in three main countries (i.e. EU, JP and US), Table 4.7 shows the model results using the whole set of countries in each cluster[17] (EP_all). This variable is obtained by calculating the share of patents from each country of origin in each cluster, multiplied by the tax-inclusive fuel price of each country. Again, the coefficient signs and significance are almost the same using the two variables.

Finally, Table 4.8 shows the results using fuel taxes instead of tax-inclusive fuel prices. However, due to the availability of fuel tax data, the period of study is reduced (1986-2008). Also in this case the models show similar results to those obtained using tax-inclusive fuel prices. This result provides an insight into fuel tax effectiveness in fostering competition between alternatives.

4.6 Conclusions

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

Our findings suggest that tax-inclusive fuel prices, employed as a proxy for carbon tax, induce a shift from non-environmental inventive efforts towards those related to the development of alternative vehicles and we have provided insights that environmental regulation encourages a crowding out effect that favours substitution instead of complementarity among inven-

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

tive efforts. Therefore, we have highlighted the effectiveness of regulation in unlocking the automotive technological system from fossil fuel path dependent technologies.

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

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

Table 4.4: Main results of fixed-effects linear model

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

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

[a] In the first column the patent stock is calculated on green and non-green clusters. In the second column, even if we maintained same variable names, the clusters are both green. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5: Correlation between percentage of patents per year in each environmental inventive activity.

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

Table 4.6: Model results using different moving averages (3, 4, 5 years)

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

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

Table 4.7: Model results using a different policy variable

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

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

Table 4.8: Main results of fixed-effects linear model using fuel taxes as policy variable (1986-2008)

	Gr vs. non-Gr		GR vs. Gr	
EP (t-1)	3.0881***		2.7583***	
	(0.8834)		(0.5844)	
ET (t-1)		11.9629**		12.0665***
		(5.3684)		-35.284
PROX (t-1)	-0.2309***	-0.2315***	0.0008	-0.0007
	(0.0132)	(0.0133)	(0.0033)	(0.0032)
CIT (t-1)	-0.1197*	-0.1267*	-0.0249**	-0.0279**
	(0.0649)	(0.0650)	(0.0108)	(0.0109)
NoF (t-1)	0.0389	-0.0025	0.0125	-0.0122
	(0.1017)	(0.1012)	(0.0688)	(0.0690)
PS g (t-1)	0.1071***	0.1084***	0.0065	0.0168***
	(0.0040)	(0.0041)	(0.0052)	(0.0044)
PS ng (t-1)	-0.0201***	-0.0030	0.0082*	0.0175***
	(0.0074)	(0.0055)	(0.0043)	(0.0037)
_cons	406.5658	1294.4763*	-85.1920	724.8870
	(656.7143)	(731.0743)	(433.4057)	(483.1778)
N	4830	4830	2070	2070
r2	0.4970	0.4960	0.4431	0.4399
F	8.2160	8.1272	9.2941	94.890

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

Chapter 5

Conclusions: summary of results

The transformation of the automobile towards sustainable transportation is an important objective to be achieved in order to reduce the environmental impacts of the transport sector which is responsible for many negative environmental externalities, impacting local and global air pollution. Indeed, the GHG emissions of the transport sector have experienced an increase of 24% during the period 1990-2008. In particular, the sector has accounted for the 19% of total GHG emissions in 2008 (EEA, 2011a).

In this thesis we have focused on the role of environmental policies in unlocking the automotive industry from fossil fuel technologies. On the one hand, environmental technologies reduce negative environmental impacts, whereas, on the other, they increase the likelihood of positive knowledge spillovers that derive from the development of environmentally-friendly technologies. Therefore, environmental policy may be the key to correcting market failures that hamper green technological advances.

In each chapter of the thesis, we have tried to fill some of the literature gaps related to the main topics that revolve around the relationship between environmental policies and environmental inventions.

In the Chapter 2, we encompassed the literature on policy-induced effects and knowledge production factors that influence the rate and direction in which knowledge is produced. We investigated the relationship between environmental policy, intrinsic characteristics of knowledge (i.e. potential stock of environmental knowledge and knowledge compositeness) and green patenting activities. In doing so, we collected patent data through an innovative methodology that detects for each patent family the 'prior' patent, i.e. the earliest patent application within the patent family. This methodology enabled us to detect the inventive activities pursued to comply with the European environmental policy framework.

In order to unpack the box of environmental inventions, discerning between different technological fields that characterise inventive activities, we built a technology space using SOM technique. The output of this process was a distance-based patent map where the patents previously collected are mapped in order to identify patents that are related to the same technology. This step allowed us to measure, through a second application of the SOM, the technological proximity between assignees using their inventive efforts in each technological fields. Therefore, employing this measure of technological proximity between assignees we calculated the potential stock of environmental knowledge assuming that the lower the cognitive distance between assignees, the higher the likelihood that they may communicate, understand and process the knowledge produced by others successfully. In addition, we investigated the dynamic patterns of knowledge advances produced by assignees, iterating the SOM algorithm for each year. In this way, we measured the assignees' movements within the technology space in order to test whether changes in knowledge compositeness influenced the development of environmental inventions. Finally, in the third application of the SOM technique we built a continuous variable that captured the increasing stringency of European emission standards, that are usually introduced in empirical models through dummy variables.

The hypotheses tested provided evidence of a positive impact of environmental policies and intrinsic characteristics of knowledge on environmental knowledge production. Going deeper into the analysis, we found that European environmental policies, 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 addition, 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 inventions. 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. The chapter provides some insights into how cognitive proximity between produced knowledge is one of the main features to be considered in the study of what triggers environmental patent production. That is, the closer two assignees are placed in the technological space, the greater the possibility of undertaking 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. Moreover, the effects of environmental policies on the development of green inventions 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 consider the influence of domestic and foreign regulations on inventive activities and the fact that, whereas domestic assignees are likely to find long-term solutions to comply with domestic regulations, foreign assignees needs to match the requirements imposed by the domestic and foreign environmental policies that regulate home and foreign markets. This may explain why the environmental policies considered in this chapter have a greater impact on European (home) assignees than on foreign ones. In addition, our findings have confirmed that both European and extra-European assignees anticipate the effective implementation of general regulatory policy instruments by actively increasing their inventive performance when legislation is announced.

In Chapter 3 we investigated the effects of policy implementation on technological knowledge related to electric and hybrid vehicle technologies. By focusing on a particular technological trajectory, we were able to assess how technological knowledge evolved over time. In this chapter we provided an empirical investigation of the evolution patterns, i.e. variation, selection and retention. In doing so, we carried out a patent citation network analysis that allowed us to assess the dynamics of technological knowledge advances. From a methodological perspective, we first used the number of technological classification code combinations as a proxy for technological varieties that the community of technologists proposed to the selection environment. Once the variation pattern had been defined, we measured selection through citations to previous patents. Our findings suggest that in the years that followed the introduction of Zero-Emission Vehicles (ZEV) legislation, many efforts were made to provide a solution to technical problems of these vehicle technologies, such as limited travel range, costs and speed, combining different bits of technological knowledge. The number of variations proposed to the selection environment by inventors increased from the beginning of the 1990s (years in which the ZEV legislation was introduced and tightened) highlighting that an explorative phase had begun in which the community of technologists tried to address the abovementioned technical hurdles. Subsequently, at the end of the 1990s, although the number of new variations stabilised, the selection of these variations increased. This may be interpreted as the beginning of an exploitation phase in which the variations presented to the selection environment were selected.

Furthermore, in the chapter, we investigated 'what' has been selected and retained in electric and hybrid car evolution through main path analysis. Hence, we applied a method proposed by Hummon and Dereian (1989) for examining connectivity in citation networks. Hummon and Dereian (1989); Hummon and Doreian (1990) developed three indices for identifying the main stream of knowledge within directed networks, i.e. the Main Path analysis. In order to define the importance of links and nodes in the network, the Search Path Count (SPC) algorithm (Batagelj, 1991, 2003) has been implemented within Pajek, a software that enables the analysis of large networks. After building a citation network in which each patent constitutes a node and citations among patents the arcs, we calculated the weight of each arc using the SPC algorithm. These weights were then used as a measure of importance of the single arcs on the whole network. Indeed, the algorithm builds on the idea that the more often a source-sink path passes through an arc, the greater the importance of that arc in the whole network (Batagelj et al., 2014). In addition, we proposed a index of knowledge retention ($IoKR$) that calculated the share of technological classification codes that were passed on from cited to citing patents. Then we combined the $IoKR$ with the main path analysis. This exercise allowed us to find more coherent connected sub-networks of nodes in which knowledge retention is higher.

The results highlighted that at the beginning of the last century, many efforts were made to improve the performance of the electric motor. In the same period, hybrid vehicles emerged from an integration of the electric motor in the conventional vehicle design. The results underline that whereas at the beginning of the century, technological advances in mechanical components characterised the development of these technologies, in recent years, a gradual shift to electric and electronic components has been experienced. Indeed, advances in vehicle system optimisation and the implementation of energy management systems has been particularly important in the evolution of these technologies.

Finally, the thesis has dealt with the potential crowding out effect of environmental technological advances at the expense of non-environmental ones. In particular, we have investigated the role of environmental policies in inducing these effects by increasing the opportunity costs that derive from real resource requirements needed to develop and adopt new technologies to comply with policy requirements.

In order to test if environmental policy stringency redirects inventive activities towards a sustainable path, driving away efforts from the development of non-environmental technologies to green ones, we collected triadic patent families filed automotive firms included in the R&D scoreboards (IRI) from the 2006-2011 editions. Subsequently, we identified the main technological fields that composed the automotive technological space mapping these patents through the SOM technique. In doing so, we were able define clusters of patents related to the same vehicle technology. In addition, we calculated the distance between the clusters that we used as a proxy for their technological relatedness. The results of the empirical analysis, carried out using a fixed-effects model, suggest that tax-inclusive fuel prices, employed as a proxy for carbon tax, induce a shift from non-environmental inventive efforts towards those related to the development of alternative vehicles. We have provided insights into the fact that environmental regulation encourages a crowding out effect that favours substitution instead of complementarity among inventive efforts.

Therefore, this represents a step forward in unlocking the automotive technological system from fossil fuel path dependent technologies.

Furthermore, relatively new to the literature, the hypothesis that environmental policies may impact competition between alternative technological efforts has also been tested. The results confirm that tax-inclusive fuel prices induce a shift from green to other green inventive activities. On the one hand, this may increase the risk of locking-in the automotive industry into suboptimal alternative technologies because at present, the technologist community is unable to identify the best alternative to the internal combustion engine. On the other hand, we must stress that there are two main technological paths within the environmental technological domain identified by the clustering exercise proposed in this chapter. The first relates to the greening of the conventional internal combustion engine vehicle, whereas the second regards the development of alternative vehicles. This result may, at least in part, be explained by the presence of competition between conventional and alternative vehicle designs even within the green technological domain.

In conclusion, our contribution has provided evidence of the positive effect of environmental policies on environmental inventions that allow the transformation of the automobile towards more sustainable designs. However, in order to unlock the automotive industry from fossil fuel path dependence, additional research efforts should be devoted to assessing the capability of environmental policy to redirect technological advances towards low-emission vehicles. In particular, the impact of environmental regulation on competition between internal combustion engine and alternative vehicle technologies, and especially, between alternative low-emission vehicle technological developments should be further explored in order to reduce the risk of locking the automotive industry into an alternative suboptimal technology. This represents one of the main objectives for on-going development of the contents of the thesis.

Appendix A

CPC subclasses

List of CPC subclasses and their description:

Table A.1: Description of clusters.

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

SOM

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, 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' 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, 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.

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 (W_v) 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:

$$Wv_{t+1} = Wv_t + \theta_{v,t}\alpha_t(D_t - Wv_{(t)})$$

Where Wv_{t+1} is the node weight at time $t+1$, while Wv_t is the node weight assigned in the step before. D_t is the input vector (patent count of each firm in each technological field – single row of the previous table) and, as explained above, $D_t - Wv_{(t)}$ 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 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 the previous formula.

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.

Appendix C

IPC subclasses

Table C.1: Description of clusters.

Electric Vehicles	
B60L0011	Electric propulsion with power supplied within the vehicle.
B60L0003	Electric devices on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. speed, deceleration, power consumption.
B60L0015	Methods, circuits or devices for controlling the propulsion of electrically-propelled vehicles, e.g. their traction-motor speed, to achieve a desired performance; Adaptation of control equipment on electrically-propelled vehicles for remote actuation from a stationary place, from alternative parts of the vehicle or from alternative vehicles of the same vehicle train.
B60K0001	Arrangement or mounting of electrical propulsion units
B60W001008	Conjoint control of vehicle sub-units of different type or different function including control of electric propulsion units, e.g. motors or generators
B60W001024	Conjoint control of vehicle sub-units of different type or different function including control of energy storage means
B60W001026	Conjoint control of vehicle sub-units of different type or different function for electrical energy, e.g. batteries or capacitors
Hybrid Vehicles	
B60K0006	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines
B60W0020	Control systems specially adapted for hybrid vehicles, i.e. vehicles having two or more prime movers of more than one type, e.g. electrical and internal combustion motors, all used for propulsion of the vehicle
B60L000710	Electrodynamic brake systems for vehicles in general. Dynamic electric regenerative braking
B60L000720	Electrodynamic brake systems for vehicles in general. Braking by supplying regenerated power to the prime mover of vehicles comprising engine-driven generators
B60L000722	Electrodynamic brake systems for vehicles in general. Dynamic electric resistor braking, combined with dynamic electric regenerative braking

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