A Semiparametric Panel Data Analysis of Green Inventions and Environmental Policies

Abstract

Innovation is a primary engine of sustainable growth. It contributes to compensate the emission increases by enhancing environmental productivity. This paper provides a new econometric policy evaluation assessment of green technological patterns and estimates a green knowledge production by exploiting a 30 years' large panel dataset of high-income countries. Because the high degree of uncertainty surrounding the Data Generating Process and the likely presence of nonlinearities and latent common factors, it considers semiparametric panel specifications that extend the parametric multifactor error model and the random trend model and adopts a recently proposed information criterion for smooth model selection to compare these semiparametric models and their parametric counterparts. The results indicate that (1) the semiparametric additive specification with individual time trends, i.e. a *semiparametric random trend model*, emerges among the set of potential models, (2) threshold effects and nonlinearities are relevant features of the data which are obscured in parametric specifications (3) the effect of a binary environmental policy on air pollution is significant and it is clearly heterogeneous when modelled as a nonparametric function of some knowledge inputs. More precisely it is found evidence of a nonlinear inducement policy effect, occurring through R&D activities. The modelling framework is aimed at enhancing the understanding of long-run innovation phenomena and setting new and more flexible policy evaluation tools.

Keywords: Innovation, knowledge, environmental policy, policy assessment, policy heterogeneity, large panels; cross-sectional dependence; factor models; random trend model, nonparametric regression; model selection.

1. Introduction

Economic and environmental sustainability is largely driven by technological and policy patterns (EEA, 2020). The achievement of a decarbonised, resource and energy efficient economy strictly depends on the generation and global diffusion of technological innovations (UNIDO, 2016, 2018). While technological progress has mostly been incremental over time, in some historical moments, technological improvements have been revolutionary, transforming the technological and skill structure of the economies. Smooth technological trajectories and discontinuities appear as a result of market, policy and institutional factors (Dosi, 1982). The major technological drivers of this age and the past three decades are the intensification of information and communications technologies, the rise of Internet of Things, the development of automation and robotics.

The green economy techno-organizational development can be seen as another innovative step in the *'shifting outward the production possibilities frontier for some generalised aggregate of potential human wants'* (Griliches, 1990, p.1669). where both continuous changes and discontinuities are present and where market and policy oriented explanations of the innovative process are necessary. Indeed, green economy trajectory characterises itself as a new socio-technical paradigm with some incremental patterns and some strong discontinuities, which depends on the policy evolutions since the 70-80-90s, when the milestone conventions took place and first policies were set (e.g. US Clean air acts, 1987 UN Convention on Sustainable Development, 1992 Rio Convention, etc..). Environmental policies, which have increased in stringency over time (D'Albrizio et al. 2017) have evolved through a different series of steps depending on the market and political cycle, more than along a smooth pattern. Within this large picture, the role of green technologies aimed at the technological and sustainable transition needs to be investigated through a medium-long run perspective, in connection to the evolution of the policy settings. A recent milestone event, the COP_{21} held in Paris in 2015 emphasised innovation challenges, with focus on radical technological solutions for clean energy and expansion of R&D expenditures aimed at boosting green innovations.

The induced environmental policy technological progress (Milliman and Prince, 1989) has found space in the history of environmental policy and international agreements. Starting with the key Kyoto Protocol milestone, it referred only once to *'Research on, and promotion, development and increased use of, new and renewable forms of energy, of carbon dioxide sequestration technologies and of advanced and innovative environmentally sound technologies'* (article 2 –a4), it created expectations of more stringent targets favouring invention & innovation development and, through the Clean development mechanisms' and Joint Implementation' flexible mechanisms, generated a market setting for international exchanges of technologies and related spillovers (Johnstone et al. 2010; Dechelezpretre et al. 2011).

Crises sono legate al modello che stimiamo? Magari le si possono introdurre attraverso il discorso dei "unobserved common factors" che "heterogeneouly affect the counries"

Crises of various feature can convey additional stimulus to technological development. First, economic crises bring about market 'destruction and creation'. Second, policy intervention to sustain the is another piece of the discourse. In 2009, the G20 proposed 'Green recovery packages' to tackle the downturn that were heterogeneously implemented by countries, a sort of global green new deal, with specific reference to the technological effects of ecological tax reforms. After 10 years of low growth and perceived fears of 'secular stagnation', the EU launched in December 2019 the European Green Deal, a set of 'Measures accompanied with an initial roadmap of key policies range from ambitiously cutting emissions, to investing in cutting-edge research and innovation, to preserving Europe's natural environment. Supported by investments in green technologies, sustainable solutions and new businesses, the Green Deal can be a new EU growth strategy'.

Technological innovations are thus intimately linked to general sustainable growth paths (Brock and Taylor, 2010). On the basis of the aforementioned discussion, econometric models should represent in a meaningful and flexible way the complexity of green knowledge generation. Nonlinear dynamics, policy effects, among other things, all cornerstones for a full understanding of the innovation-policy transition and evolutionary path. More specifically, it is worth studying whether and how innovation inputs produce nonlinear effects on inventions, whether and how unobserved factors additionally affect the way knowledge is produced, and in this framework, whether and how policy affects the creation of new knowledge.

Within this framework, this paper examines a model of Green Knowledge Production functions (GKPFs, see e.g. Charlot et al, 2015), to address the possible *functional form bias* and *correlated unobservable factors* bias that may arise when adopting standard parametric fixed effects approaches. To do so, it considers semiparametric panel specifications, that are rarely applied to address environmental and development issues (Millimet et al. 2003; Mazzanti and Musolesi, 2014), with interactive fixed effects. In particular, it extends the parametric random trend model (Heckman and Hotz, 1989) and the Common Correlated Effects approach (Pesaran, 2006), which have been also shown to be useful for policy evaluation (Fujiki and Hsiao, 2015; Wooldridge, 2005).

A specific focus of this paper is assessing the effect of environmental policy on green inventions. In so doing, while a common practice in the policy evaluation literature consists in focusing attention on the mean effect or imposing a homogeneous effect across units, along the lines depicted by Cardot and Musolesi (2019), we also consider a model in which the effect of the policy is expanded as a nonparametric function of some key covariates (innovation inputs), in order to highlight possible *heterogeneous policy effects*, which are missed when focusing on mean effects. In other words, we allow for a nonparametric interaction between the discrete policy and the knowledge inputs. The rationale behind such a modelisation relies on the presence of absorptive capacity and a possible non neutral effect of environmental policy. Indeed, we could expect that environmental policy is transmitted to technological performances, with a significance and strength which depends on the country specific investments in knowledge driving factors.

The model also allows for spillovers effects, consistently with the Griliches legacy (Griliches, 1992), who emphasises the role of 'the magnitude' of R&D spillovers, and with a relevant bulk of literature on R&D international spillovers (Ertur and Musolesi, 2017) and on the KPF, estimated at different levels of aggregation (Charlot et al, 2015).

Cross-sectional dependence is introduced as a result of a finite number of unobservable common factors that may have different effects on knowledge creation across countries. Such factors might include, for instance, aggregate technological shocks, global crises, global policies intended to raise the level of technology or energy price shocks. The heterogeneous effect of these factors may be the result, for instance, of country-specific technological constraints (Ertur and Musolesi, 2017).

Finally, due to the high degree of uncertainty surrounding the true Data Generating Process (DGP), and the bias-efficiency trade-off when comparing parsimonious to complex models (Almeida et al. 2018; Racine and Parmeter, 2014; Ma et al., 2015), the paper adopts a recently proposed information criterion for smooth model selection (Wood et al, 2016), to compare some alternative semiparametric models with more common parametric specifications.

In summary, the two main research directions are:

- Assessing the functional form of green knowledge generation by focusing attention on Model uncertainty, Nonlinearities and Unobserved common factors.
- Analyzing interactive and heterogeneous policy effects.

Regarding policies, we exploit official OECD sources. By constructing indicators on the basis of raw OECD data, the policy dataset is admittedly longer in the time dimension compared to the OECD EPS policy indicator (Albrizio et al. 2017), which does not cover the 80's. It is worth noting that, though energy prices might be a sound alternative to environmental and energy policies (Sato et al. 2015, Popp, 2002), the use of environmental policy categories, that capture how policy intensity has evolved over time allows assessing threshold effects, that highly characterise the dynamic efficiency effects of policies. Energy prices, as a measure of policy, also capture market distortions related to the energy market, endowments of fossil fuels, etc..

The paper is organised as follows. Section 2 summarises some related literature and discusses some stylized facts on green inventions and policies. Section 3 presents the overall empirical setting of reference, with emphasis on model selection and the features of semiparametric models. Section 4 comments on the main results of estimation. Section 5 extends the model by allowing for heterogeneous policy effects within a nonparametric and flexible approach. Section 6 concludes and provides hints for further research.

2. Related literature

The introduction highlighted that the macroeconomic evidence on the GKPF deserves further and specific analysis. This paper aims at providing new knowledge by providing an econometric analysis that grounds on, but tries to advance, from seminal works on induced innovation effects in the energy-environmental framework (Popp, 2002). It complements recent papers that examine 'directed technological change' by observing clean technologies and policies with a focus on micro and sector based evidence. Among seminal papers, Acemoglu et al. (2016) analyse the transition to a decarbonised economy through technology and estimate the model by using firm level US energy sector data; their focus is on the role of carbon taxes and subsidies to stimulate a transition. Aghion et al. (2016) complement that analysis and provide evidence on the automotive industry sector, finding signs of path dependency in clean technological innovations, but also significant fuel tax effects. Other recent works examine specific policy realms, such as the EU emission trading (Martin et al., 2014a, Calel and Dechelezpretre, 2016); carbon taxes effects on manufacturing sector innovation (Martin et al., 2014b) or specific environmental realms such as given renewable energy (Nesta et al. 2014). The rationale of those type of studies is to deeply analyse specific policy effects on diversified clean technologies.

The paper takes a broader macroeconomic and longer run perspective on green economy technological dynamics. It tries to add knowledge through the implementation of econometric advancements in the framework of green knowledge production functions (GKPF) that use patents as best proxy of innovation at macroeconomic level (Griliches, 1990). Popp (2019), who conveys a critical survey of the literature on environmental policy and innovation, recently notes, *patent counts not only serve as a measure of innovative output, but are indicative of the level of innovative activity itself*. The present work focuses on a relevant set of high-income countries due to our interest in examining green inventions and environmental policies dynamics over 30 years. Though the role of emerging and developing countries in producing green knowledge has increased over the past decades (Dechelezpretre et al. 2011) and technology transfers are crucial to achieve global sustainability (Popp, 2012), most innovation is still concentrated in a few more advanced countries, that currently present a consolidated history regarding the evolution of environmental policies stringency.

3 Data and stylized facts

3.1 The Data

The dataset is a balanced panel dataset covering the period 1982-2012 for 19 OECD countries. As far as the dependent variable is concerned, green patents (GK) are collected from OECD-STATS databases. We consider patents which come under Selected Environment-related Technologies as defined by OECD (IPC: ENV_TECH) and granted at USPTO (United States Patent & Trademark Office), and calculate the number of patents country-wise according to the inventor(s)'s country(ies) of residence. Patents of an agent belonging to country i but submitted to country j are accounted as i-related patents. For each patent we have information on the patent family, year of filing and the geographical location of the inventors [1]. In this paper, fractional counts are used in order to avoid double counting of the same inventions across different geographical areas. This means that if a patent family is developed by more than one inventor, we weight that patent family according to the geographical areas of the inventors.

[1] Fractional counts are used in order to avoid double counting of the same inventions across different geographical areas. This means that if a patent family is developed by more than one inventor, we weight that patent family according to the geographical areas of the inventors. Patent family also capture a feature of 'quality' of patents at macroeconomic level.

As far as explanatory variables are concerned, we use the knowledge input set following Charlot et al. (2015). Research and Development (RD) and Human Capital (HK), are both included as stock factors. Specifically, we use Gross Domestic Expenditure on Research and Development (GERD) flow values, collected from OECD-STATS database, using total data as source of funds and data are in 2010 Dollars - Constant prices and PPPs. Missing values are filled in similar way as of Coe and Helpman (2009), and then we calculate GERD stock values using perpetual inventory method as in Coe and Helpman (1995) assuming depreciation rate to be 0.05. HK stock is collected from Penn World Table version 9.0 (Feenstra et al., 2015).

To account for knowledge spillovers in the green patenting realm (Verdolini and Galeotti, 2011) we also consider foreign RD and foreign HK (WRD and WHK, respectively). We use geographic proximity as a channel of technology diffusion for its consistency with theory (Keller, 2002) and for exogeneity reasons as it may be considered an exogenous proxy for some endogenous measures of socioeconomic, institutional, cultural or linguistic similarities that might enhance the diffusion of technology. Following Keller (2002) and Ertur and Musolesi (2017), we use an exponential decay function.

Policy indexes are derived from OECD raw sources and used as key policy indicators (Nesta et al. 2014), as also stressed by Johnstone et al. (2010) "due to the heterogeneous nature of the data, it is not possible to construct continuous variables in which the level of "stringency" (or "support") is commensurable across policy types and countries. As such, for most of the policy types dummy variables are introduced to capture the effect of the implementation of different policies".

Specifically, the base information refers to six policy categories over a broad spectrum which incorporates the multidimensionality of policy efforts (OECD, 2016): deposit refund schemes, fees, Tax Rates of Environmentally Related Taxes, tradable permits, voluntary approaches, environmentally motivated subsidies (https://pinedatabase.oecd.org/). On the basis of the 6 categories which are observed year by year and assume values 0 or 1, a policy indicator assumes a value of 1 in the year of the introduction of a policy among the six. If policies are introduced in a given year in the country, the indicator increases by one for each additional policy up to the 6 level value. The EP treatment variable we use in the paper is derived from the aforementioned indicator, potentially ranging from 0 to 6, and takes the value 1 if at least one policy is introduced. Finally, we note that while information is available for three domains: air pollution, climate change, energy efficiency, we focus in this paper on the domain of air pollution, given the relative longer history of air pollution policies over the considered period.

To address heterogeneous effects within a similar framework as in Cardot and Musolesi (2019) but with the limitation in terms of sample size of using macroeconomic data, we decide to rely on a binary treatment (0/1) variable rather than using a categorical variable with multiple categories.

3.2 Stylized facts about green inventions and environmental policies

As the previous paragraphs noted, nonlinear dynamics, cross-country heterogeneity and common latent factors characterise real world innovation phenomena. The section outlines some time patterns and heterogeneous trends.

Figure 1 shows that the green patent pattern has shown some nonlinear dynamics for all countries, which experience a rather common nonlinear, exponential-type, evolution of green patent creation, albeit with different intensities. Indeed, while for most of the countries, green patents follow a smooth exponential pattern, for others, they evolve around a rather linear trend (Australia, Canada, Denmark, Finland and Germany, to show diversified examples among others), and finally, for some few other countries, they show a very deep increase after a period of stagnation (South Korea, Portugal, Greece, Ireland, but also Sweden[2]). The observed patterns are coherent with a relatively earlier adoption of policies in more mature economies, that has produced a smoother evolution, compared to some others that had lower income at the beginning of the environmental

[2] This example shows that country heterogeneity is relevant even within similar 'clubs' of countries (Scandinavia, as well as the EU economy or Anglo Saxon countries). Sweden, one of the first countries to address climate change and sustainability through policies, shows an increasing but highly nonlinear invention pattern.

policy dynamics. The latter set of countries have substantially closed gaps in terms of GDP and policy commitment as well. This is noteworthy, since it shows that environmental policies, having an international dimension in the realms of pollution and emissions, can act as an additional lever of convergence, through innovations.

As far as R&D stock is concerned, nonlinear increasing trends are also a feature of the data (Figure 2). It is worth to mention that the achievement of a R&D/GDP ratio of 3 % is one of the five headline targets of the 'Europe 2020' strategy for a smart, sustainable, inclusive growth. EEA (2020) points out that: "In 2017, gross domestic expenditure on R&D (GERD, Gross Domestic Expenditure on R&D) of all sectors in EU-28 countries has been EUR 317 billion, corresponding to 2.06 % of GDP, a figure higher than the 1.77 % of 2000 but well below the 3 % target of Europe 2020". However, within the EU and worldwide, as a consequence of an extremely high cross-country heterogeneity in terms of R&D investments, the increase of R&D stock from the beginning to the end of the period varies greatly across countries. While in in Italy, it grows of about 20%, in South Korea, it increases of more than 200%.

Finally, looking at the policy variable EP (air pollution policies), overall, 45% of the observations are treated units. While the ex-ante logic of building such a kind of policy variable is explained in the previous section, ex-post, having two homogeneous groups in terms of size can be useful in order to estimate the model. Moreover, EP shows relevant variations in both the time and the cross-sectional dimension (Figures 3 and 4). Indeed, while very few observations were treated at the beginning of the period (0% in 1982, 5% in 1983) almost 80% were under the environmental policy in 2012. OECD (2016)[3] observes that 'Environmental policy stringency has been increasing in all OECD countries and BRIICS over the past two decades' and 'Policies, as measured by the EPS indicator, are most stringent in Nordic countries, the Netherlands, Finland and Germany. Among OECD countries, they are least stringent in Greece, Portugal, Ireland and Hungary. Most of the other countries are close to the OECD average' (p.6). We further note following Botta and Kozluk (2014), that the 1995-2012 increase is larger for highest OECD (Finland, The Netherlands, Denmark) that lowest OECD (Greece, Portugal, Ireland). Analogies with the aforementioned invention patterns are highlighted. The heterogeneity goes further anyway: due to diversified starting points and 1995-2014 increases, some more mature countries in the EU and the Anglo Saxon world are below the OECD average, such as France, Italy, Australia, UK, USA, while some initial laggards have moved up higher than the average, such as Spain, Slovakia, Poland, Korea (Botta and Kozluk, 2014).

Moreover, in view of estimating the model, we globally do not observe serious problems in terms of lack of overlap. Having observations that are out of support may affect the performance of regression approaches, mainly by affecting their precision (Lechner and Strittmatter, 2017). However, using flexible regression models, which are able to fit locally the data, is an effective way to address such a potential issue.

In summary, we highlighted the presence of nonlinear and heterogeneous trends in green patents, environmental policies and R&D stock. The existence of latent common factors that can heterogeneously affect the different countries as a results of an increasing process of globalization to whom each country idiosyncratically reacts is a source of cross-sectional dependence. *Nonlinearities*, *latent common factors* and possibly *heterogeneous policy effects* are all handled in the econometric framework presented in the next section.

[3] OECD, 2016, How Stringent are environmental Policies?, OECD Report.

Figure 1 -Trends in green patenting per million inhabitants over time (for countries in the top quintile)

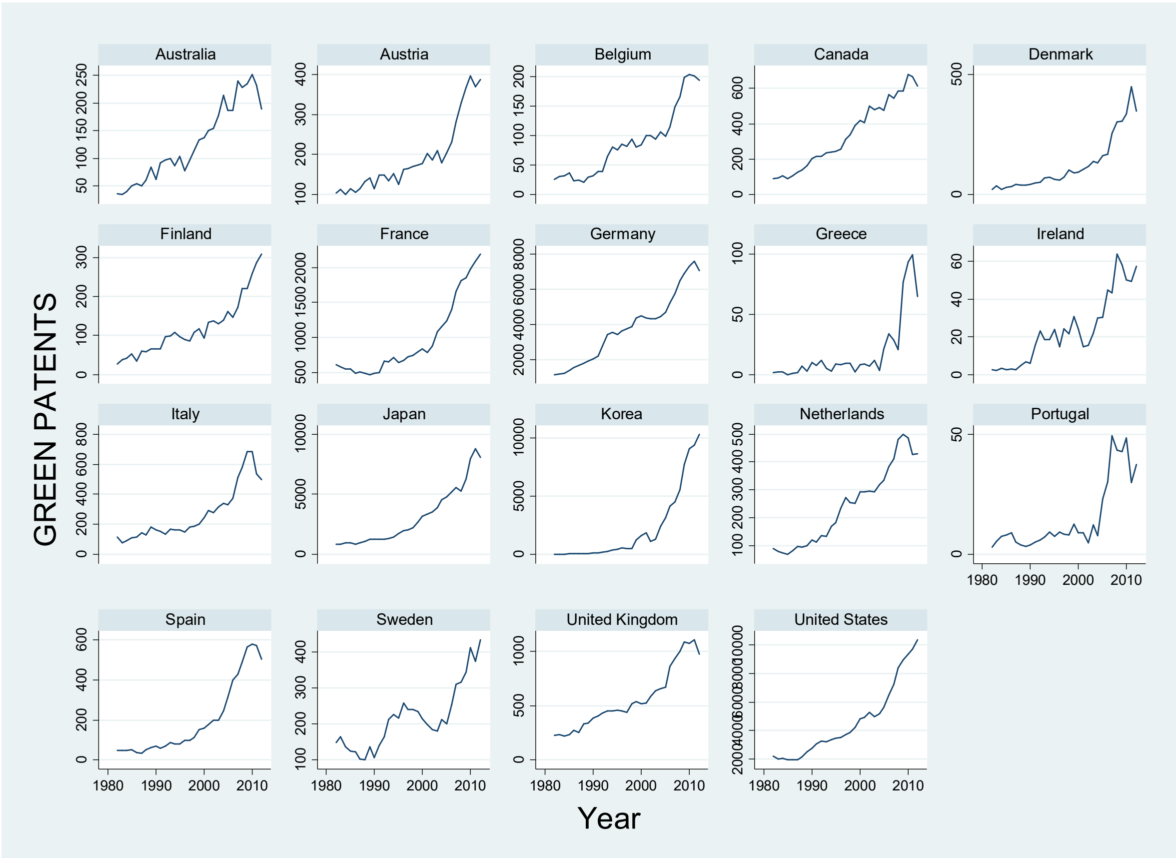
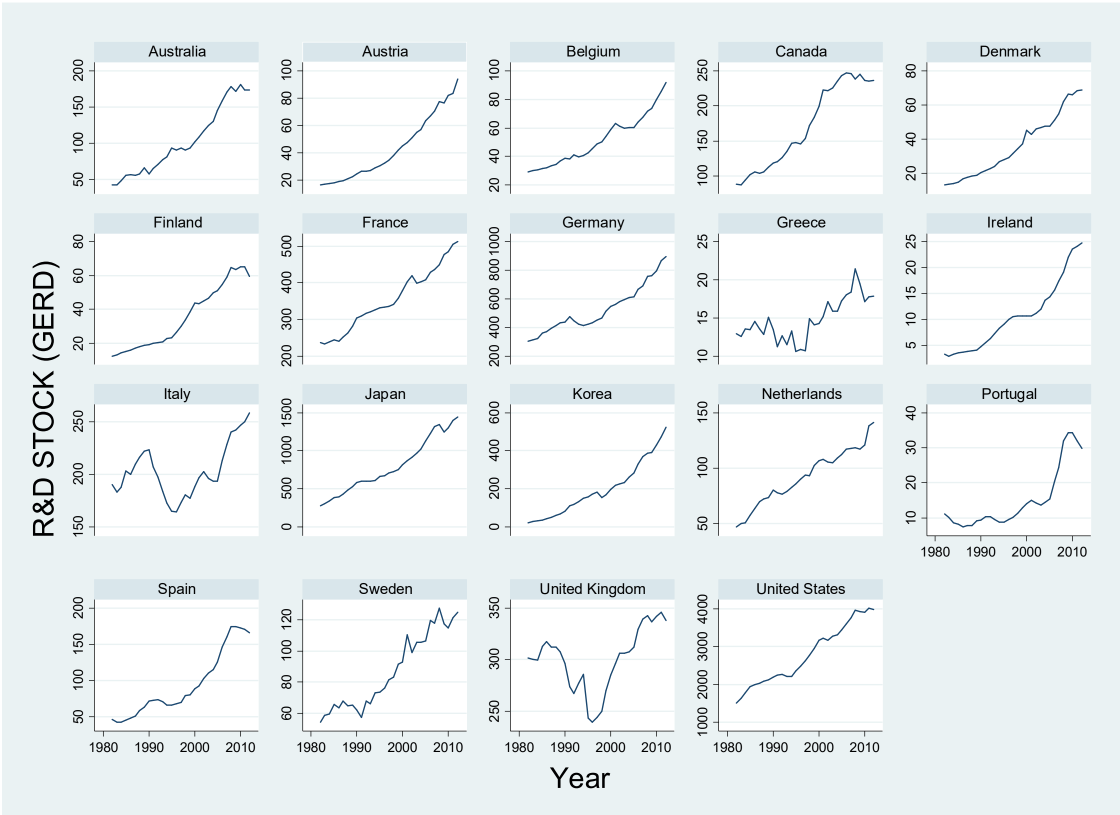
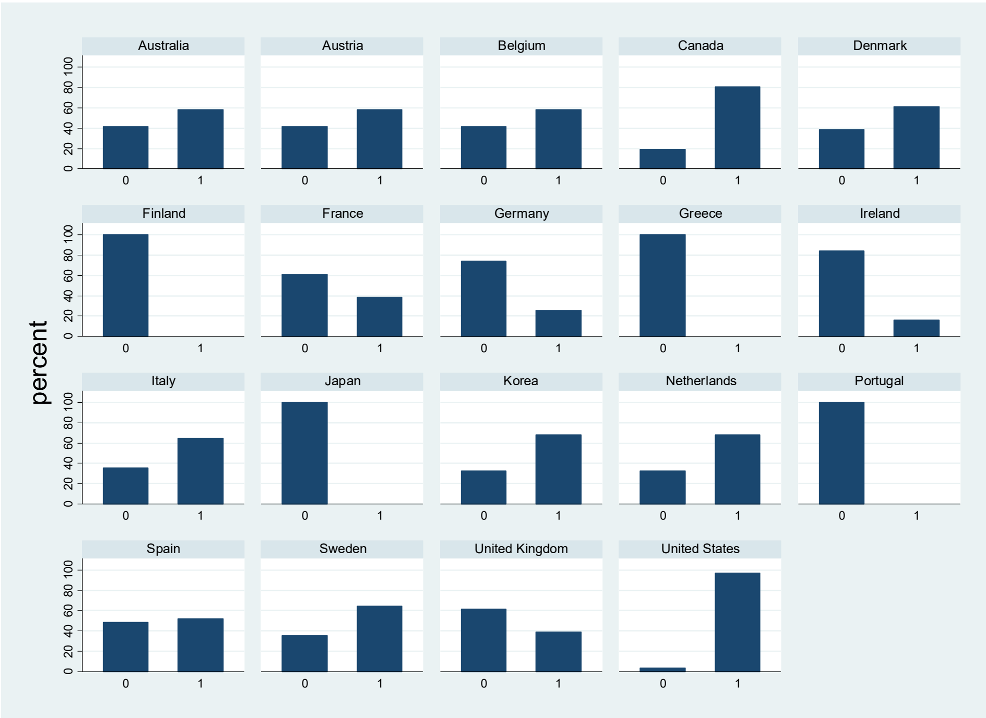
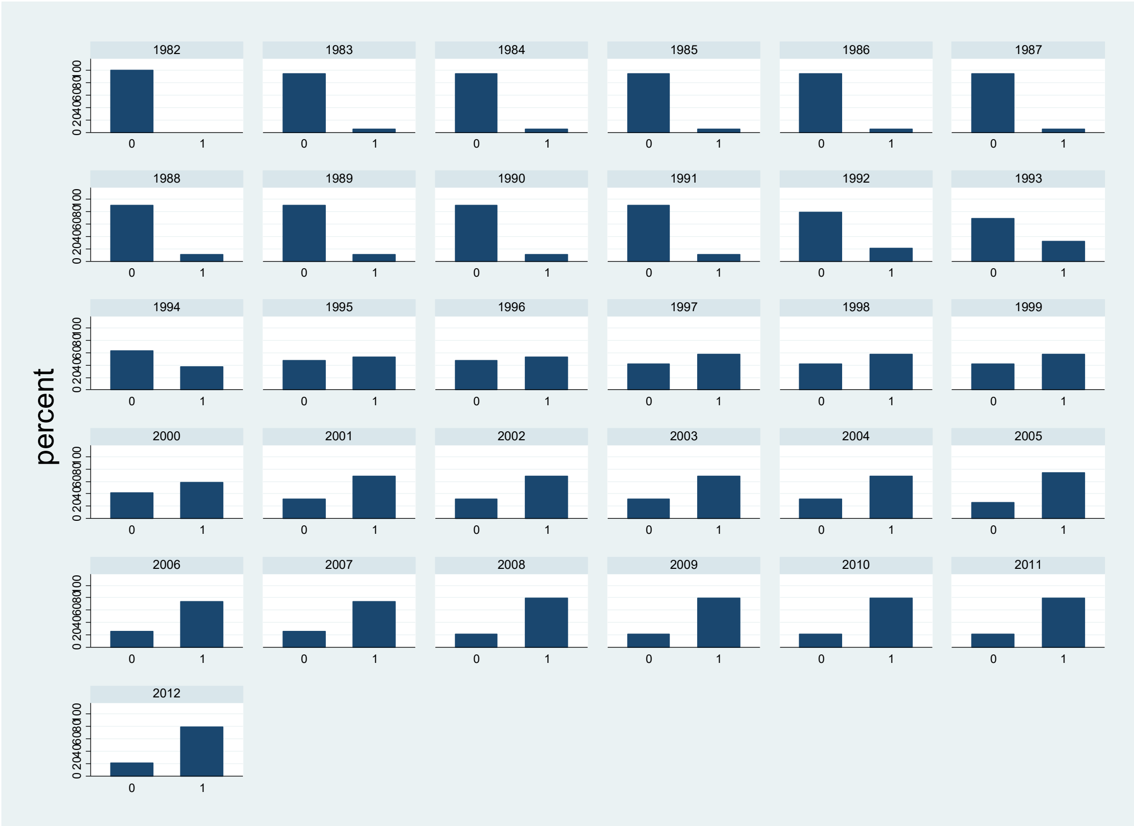


Figure 2 -Trends in R&D stocks (public and private R&D)



Figures 3-4 -Trends in air pollution policy indicator (binary, constructed from OECD raw data)





3. Semiparametric modelling of green knowledge production and environmental policies

The modelling framework is aimed at enhancing the understanding of long-run knowledge generation and setting new policy evaluation tools. As the introduction commented on, modelling the complexity of the innovation process has been a challenge of empirical analyses in all realms, given the likely presence of complex nonlinear relations, latent common factors and heterogeneous relations (Charlot et al, 2015). Relaxing simplistic assumptions regarding how innovation is generated and analysing the link between policies and green innovations may produce additional insights for research in this field. In order to model the GKP, we propose to consider the following rather general semiparametric panel data model:

$$
\begin{aligned}
GK_{it} &= c_i + \beta EP_{it} + g\left(RD_{it}, HK_{it}, WRD_{it}, WHK_{it},\right) + \nu_{it} \\
\nu_{it} &= \gamma_i' f_t + \varepsilon_{it}
\end{aligned}
\qquad (1)
$$

where GK_{it} measures green patenting activities, g is a real unknown function, RD_{it} and HK_{it} refers to the two main expenditures behind inventions, namely R&D and human capital investments[4]. WRD_{it} and WHK_{it} are introduced to take into account of some spillover effects that may arise from both R&D and human capital from foreign countries. Finally, EP_{it} is the binary indicator of policy intensity described in the previous section.

[4] It is here worth citing Griliches (1990, p.1674) who stresses that ‘patents tend to taken out relatively early in the life of a research project’. In the green realm, the empirical literature has noticed that patenting activities arose pretty early along the first environmental policy phases in the 80’s and 90’s (Jaffe et al. 1995; Jaffe and Palmer, 1997).

Note as well that errors v_{it} have a multifactor structure (Pesaran, 2006 and Su and Jin, 2012) , f_t being a vector of unobservable common factors with heterogeneous factor loadings γ_i' ,and ε_{it} is the idiosyncratic error term. It is relevant to observe that f_t is modelled as to be correlated with the explanatory variables (Pesaran, 2006; Ertur and Musolesi, 2017, Su and Jin, 2012).

Model (1) extends Charlot et al. (2015) since, as also stressed by Heckman and Hotz (1989), the random trend specification they adopt can be viewed as a special case of the multifactor error model (1). Obviously, by imposing homogeneous loadings parameters, a common two-way fixed effect is also obtained.

To estimate model (1) we adopt the approach proposed by Su and Jin (2012), and use spline functions to model the nonparametric part of the model, *g(.).* In particular, we adopt penalized regression splines, because they have been proven to perform well empirically and asymptotic results have been recently proven (e.g., for a more detailed discussion, Gioldasis et al, 2020).

The empirical analysis specifically addresses key methodological issues, that are discussed below.

Functional form and nonlinearities. Although a log-log specification is customary in the literature on the KPF, the precise functional form cannot straightforwardly defined from a theoretical basis and alternative functional forms cannot be excluded a priori. This relevant issue was recognised, even at the firm level, in an early work by Griliches (1990, p. 303) *"Given the nonlinearity and the noisiness in this relation, the finding of "diminishing returns" is quite sensitive to functional form, weighting schemes, and the particular point at which the elasticity is evaluated".* As highlighted by Varga (2000), it can be expected, for instance, that a critical mass of R&D or human capital is necessary to make such inputs truly effective. Moreover, not only the linearity but also the additivity assumption implicit in the linear model, might be too restrictive and should be relaxed, as suggested by Hall et al. (2010, p. 33): *"Because the additive model is not really a very good description of knowledge production, further work on the best way to model the R&D input would be extremely desirable"*. These reasons suggest that estimating a nonparametric relation between knowledge and its main inputs could be important to avoid a *functional form bias* (see, e.g., Charlot et al, 2015).

Correlated unobservable factors. The existing literature on the KPF has addressed such issues by exploiting the panel structure of the data. Generally, a two-way (individual and common time) fixed effects approach has been adopted, while Charlot et al. (2015) use a random trend specification that introduces an interaction between individual fixed effects and a linear time trend. Both approaches are special cases of the factor model considered by Pesaran (2006). The factor model has been motivated on its ability to handle both endogeneity due to unobservable, whereby the explanatory variables are allowed to be correlated with the factors, and cross-sectional dependence. Cross-sectional dependence is indeed introduced as a result of a finite number of unobservable common factors that may have different effects on knowledge creation across countries. Such factors might include, for instance, aggregate technological shocks, global crises, global policies intended to raise the level of technology or energy price shocks. The heterogeneous effect of these factors may be the result, for instance, of country-specific technological constraints (Ertur and Musolesi, 2017). The CCE approach by Pesaran (2006) explicitly allows for such a kind of cross-sectional dependence, which may pose serious problems, that is, inconsistency of standard estimation methods, and also remains valid in a variety of situation that are likely to appear (Pesaran and Tosetti, 2011; Chudik et al, 2011). Allowing for unobserved factors/time effects that might affect knowledge and being correlated with innovative inputs is crucial to avoid a *correlated unobservable factors bias*. Finally note that considering models allowing for correlation between the unobservables and the explanatory variables, such as the common factors model, the random trend model, or either commonly used two-way panel data models, is suitable to address selection bias in models with dummy endogenous variables (Wooldridge, 2005; Gobillon and Magnac, 2016; Cardot and Musolesi, 2019).

Model uncertainty. We recognise the existence of a high uncertainty surrounding the true DGP. In general, there is bias-efficiency trade-off when comparing parsimonious to complex models (Almeida et al. 2018; Racine and Parmeter, 2014; Ma et al., 2015). Considering flexible models is appealing but may come at the price of unfeasible or extremely inefficient estimates (Baltagi et al., 2002, 2003). For these reasons, we perform model selection by comparing some alternative models.

4. Main results

4.1 Model selection: parametric and semi parametric functions

Model selection is performed by applying recent advances in the topics and specifically we consider an information criterion recently developed within the framework of smooth regression models (Wood et al, 2016). We compare alternative specifications for g(.) and for the unobserved time effects. For the latter we consider three alternative specifications: common factors with heterogeneous loadings (the CCE approach by Pesaran, as extended by Su and Jin, 2012), $\nu_{it} = \gamma_i' f_t + \varepsilon_{it}$, the random trend model including individual time trends (Wooldridge, 2005), $\nu_{it} = \gamma_i t + \varepsilon_{it}$ and time dummies (two-way fixed effects), $\nu_{it} = \lambda_t + \varepsilon_{it}$. For the function g(.) we consider both parametric linear models and additive models that avoid the curse of dimensionality problem of fully nonparametric model. In total, we consider six alternative models.

The results in Table 1 indicate that the preferred model (Bayesian Information criterion selection) presents additive smooth terms for g(.) and individual time trends (random trend) to represent the latent common factors. In the following, the econometric model we adopt can be written as:

$$GK_{it} = c_i + \beta EP_{it} + g_1\left(RD_{it}\right) + g_2\left(HK_{it}\right) + g_3\left(WRD_{it}\right) + g_4\left(WHK_{it}\right) + \gamma_i t + \varepsilon_{it} \qquad (2)$$

Overall the results provide interesting insights about model selection. It is found indeed that the random trends specification always performs better than the two-way fixed effects model and the multifactor error model (CCE). This is an extremely interesting results suggesting the use of an intermediate level of heterogeneity when modelling unobserved common factors, the random trend model being more efficient but less flexible than the CCE specification. Note indeed, that the nuisance parameters to be estimated in the CCE are N*(K+1), with K being the number of explanatory variables, while the random trend requires the estimation of N nuisance parameters, one for each individual trend. Another relevant result is that the two-way fixed effects model is always dominated by the other two and performs the worst: imposing homogeneous effects of the time components appears, ex-post, a too much restrictive assumption. Finally note that in two cases out of three (the random trend and the two-way model) the specification with additive smooth terms outperforms the parametric linear model.

Two main remarks are in order. First note that the preferred model allows for an intermediate-high level of flexibility since it allows for nonparametric additive effects of the regressors along with individual trends. Both too much simple models, such as the parametric one or the two-way fixed effects, and too much demanding specifications such as the multifactor error are thus rejected (see also Baltagi et al., 2002, 2003). Second, it is worth to note that allowing for nonparametric smooth terms and individual trends provides a more credible identification of the policy effect compared to parametric models and/or a standard two-way model (for a more detailed discussion, see, e.g. Cardot and Musolesi, 2019; Wooldridge, 2005; Lechner, 2010, 2015).

Specifications	*BIC*
1. Semiparametric additive smooth functions, individual time effects (random trend)	218.1777
2. Parametric, individual time effects (random trend)	235.3614
3. Parametric, multifactor error structure (CCE)	246.0169
4. Semiparametric additive smooth function, multifactor error structure (CCE)	282.6753
5. Semiparametric additive smooth function, two-way fixed effects	476.0993
6. Parametric, two-way fixed effects	604.5955

Table 1 – Model selection outcomes

4.2 Estimation results

4.2.1 Semiparametric estimation of the GKPF: nonlinearities, threshold effects and positive average policy effect

In this section, we focus attention on the results of estimation of (1). As far as the effect of the policy is concerned, which is assumed to be constant both across countries and over time, the parameter β, which also identifies the average treatment effect (see Wooldridge, 2010), is estimated to be 0.009 (p-value=0.055). This result thus indicates a statistically positive effect of environmental policy intensity on green inventions capacity. Over the time span which embraces the second US Clean air act, the Rio Conventions, the Kyoto Protocol and the EU 202020 strategy among other policy steps of international relevance, high level of policy intensity brought about specific effects on green inventions. The outcome enriches the macroeconomic evidence that, among others, Johnstone et al. (2010, 2012) provided: in the first case over a similarly long 1978-2003 time span but focusing on renewable energy policies, and over a more restricted time span and using opinion survey based policy indicators in the second case.

The parametric evidence around the policy effect signals a significant but rather small effect, if a binary shift is considered. The 'treatment' high intensity / low intensity of the policy, which varies over time, signals that the policy intensity is relevant, but not a major driver when observing the economic significance of the effect as well. This result suggests extending the analysis of policy effects by considering the role of heterogeneous innovation investments across countries. In other words, environmental policy might be transmitted to technological performances, with a significance and strength which also depends on the country specific investments in knowledge driving factors, which become a sort of 'innovation endowments'. This extended environmental policy semi-parametric model (that will be presented in section 4.3.1) is linked to the general analysis of the endogeneity of innovation in the environmental economics realm (Jaffe et al. 1995; Jaffe et al. 2002).

The results concerning the additive nonparametric components of (1) are presented in figure 5. The three graphs depict the estimated univariate smooth functions for the significant covariates. Following Marra and Wood (2012), the estimated smooths are shown with confidence intervals that include the uncertainty about the overall mean. We also computed the p-values for smooth terms using a Wald test statistics suggested Wood (2012). These are p-values associated with Wald test that the whole function equals zero. Low p-values indicate low likelihood that the splines of the function are jointly zero. Also note that smooths are subject to sum-to-zero identifiability constraints as detailed in Cardot and Musolesi (2019).

Estimated Smooths (except WHK) appear to be highly significant, showing extremely low p-values associated to the Wald tests. Moreover, using an approximate ANOVA test procedure (see Wood, 2017), linearity is always rejected for all explanatory variables but WHK. WHK presents instead a positive linear effect, which is not statistically significant (p-value=0,27). The non-significance of WHK is also consistent with the literature focusing on international technology diffusion, which stresses on the role of R&D spillovers (Ertur and Musolesi, 2017).

Also note that the response as well as the explanatory variables are in logarithmic values: this facilitates the economic interpretation, as the slope of the estimated smooth functions represents an estimated elasticity. This also makes the Gaussian assumption more plausible, and allows for a straightforward comparison with parametric models, expressed in log-log form.

Figure 5 shows that the estimated smooth functions are highly nonlinear, with relevant threshold effects. Indeed, for all the three significant variables -- RD, HK, WRD -- a critical mass is necessary in order for ensuring an effective impact on green patenting. This result is consistent with some related literature focusing on non-green knowledge creation and/or at a different level of aggregation (Varga, 2000, Charlot, 2015).[5] Evidence for RD and HK testimonies that policy targets on these inputs are justified; in addition, as the number of countries reaching substantial knowledge investments (e.g. 3% of GDP or higher) enhance the spillover effect. In the specific framework of green energy knowledge development, Verdolini and Galeotti (2011) panel data analysis demonstrated that 'that higher geographical and technological distances are associated with lower probabilities of knowledge flow' and 'spillovers between countries have a significant positive impact on further innovation in energy-efficient and environmentally friendly technologies'.

In summary, the estimation of a *semiparametric random trend model* indicates that the long-run evolution of green inventions was effectively affected by the discrete environmental policy and by the continuous variables R&D, Human capital and foreign R&D, which show significant nonlinear monotonic patterns and relevant threshold effects. Only foreign human capital has not, at least in the present time span, an influence on green inventions.

4.2.2 A comparison with a misspecified parametric model

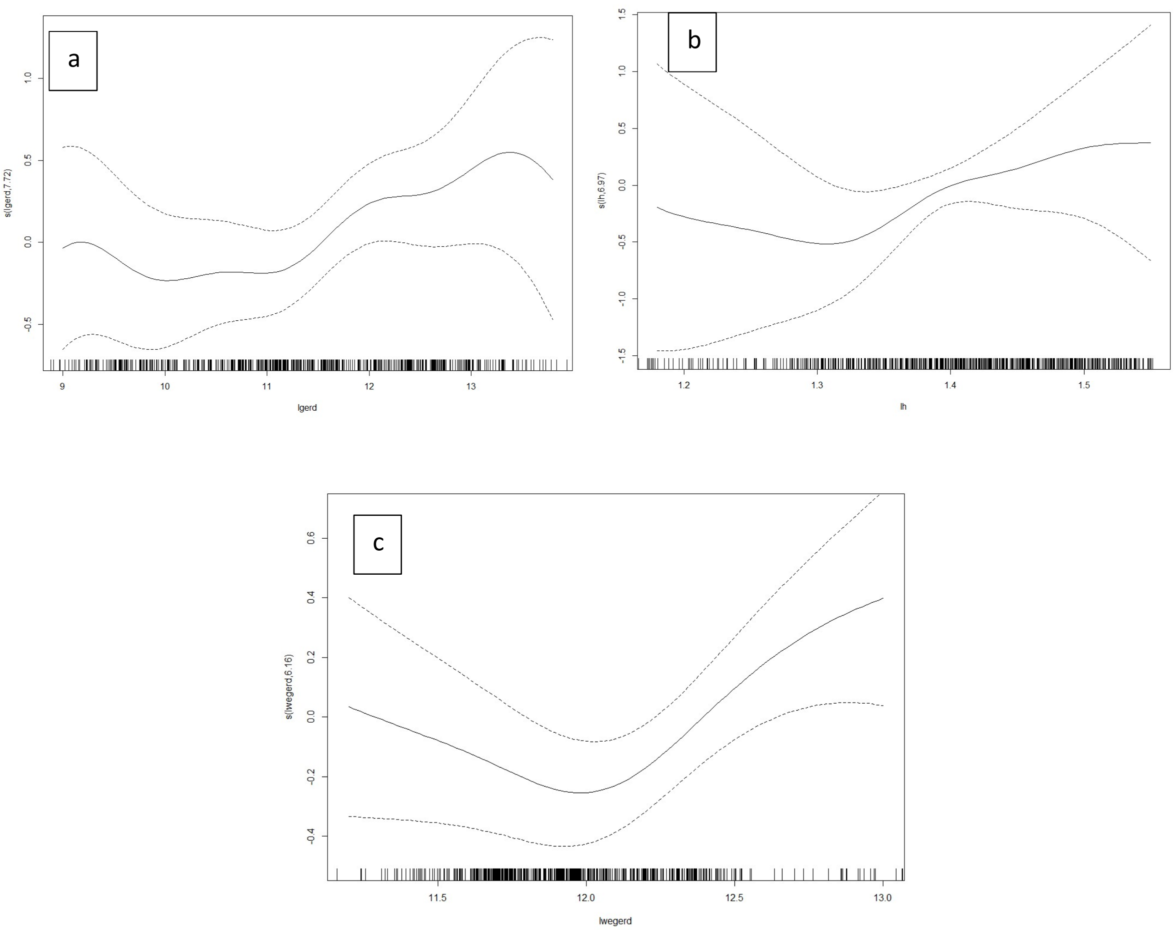
It is interesting to compare these results with those we would have obtained by erroneously imposing a parametric specification. This may provide relevant insights because, as stressed for instance by Lechner (2011), the size of the bias of misspecified parametric models can be assessed only through a comparison.

Specifically, when estimating the traditional parametric random trend model, i) the policy effect decreases substantially and becomes negative, with $\hat{\beta} = -0,0015$, and being no more statistically significant (p-value=0.97); ii) among the domestic knowledge inputs, only RD is significant at standard levels, with an estimated elasticity equals to 0,47 (p-value=1,62e-05) while human capital stock has a positive effect (0,057) but is not significant with a p-value=0.98 ; ii) the estimated coefficients associated to WRD and WHK have both the wrong (negative) sign (-0, 10 and -9,02 respectively) with WHK also being highly significant.

The above results thus indicate the importance of adopting a flexible specification to highlight significant policy effects. The same result was found, for instance in Cardot and Musolesi (2019). These estimates also suggest that adopting a flexible specification permits to get more credible and refined results with respect to the effect of the continuous knowledge inputs, since nonlinearities and threshold are important features of the innovation data. Estimating traditional parametric model would have produced a substantial *function form bias*.

[5] It is worth noting that domain of the variables has been appropriately reduced to the regions where the effects are significant. Indeed, in the regions of the domain of the variables where data are sparse, large confidence interval bands are present, since it is not possible to precisely estimate the functions of interest. These regions, where the plots cannot be easily interpreted, correspond to low levels of HK and to very low and levels of RD and WRD.

Figure 5, R&D (a), human capital (b) and RD spillovers (c) effects on green inventions– estimated univariate smooth functions



4.3 Extending the model: interactive policy effects

4.3.1. Econometric modelling

A common practice in the policy evaluation literature consists in focusing attention on the mean effect or imposing a homogeneous effect across units and overtime, as we did in the previous section. In this section, we exploit the modularity and flexibility of spline modelling to allow for heterogeneous policy effects. We consider a model in which the effect of the policy is expanded as a nonparametric function of some variables, which are selected among the knowledge inputs. Say it differently, the discrete environmental policy non parametrically interacts with some continuous covariates: in doing so, the discrete policy produces not only a neutral shift, but a more general change in the estimated nonparametric functions. This can be written as

$$GK_{it} = c_i + \beta EP_{it} + g_1\left(RD_{it}, EP_{it}\right) + g_2\left(HK_{it}, EP_{it}\right) + g_3\left(WRD_{it}, EP_{it}\right) + g_4\left(WHK_{it}, EP_{it}\right) + \gamma_i t + \varepsilon_{it}$$

In this framework, there is a binary-by-continuous interaction (Ruppert et al, 2003) allowing us to obtain two distinct nonparametric functions (one for each level of EP_{it}) for each explanatory variable and the (heterogeneous) policy effect which is defined as

$$\beta_{it} = E\left[GK_{it} \mid X_{it}, EP_{it} = 1\right] - E\left[GK_{it} \mid X_{it}, EP_{it} = 0\right]$$

is consequently a nonparametric function of the continuous knowledge inputs, X_{it}, and more specifically it can be expressed, given the vector of covariates X_{it}, with the following specification,

$$\beta_{it} = \beta + \sum_{j=1}^{p} m_j\left(X_{itj}\right) \qquad (3)$$

Where $m_j\left(X_{itj}\right) = g_j(X_{itj}, EP_{it} = 1) - g_j(X_{itj}, EP_{it} = 0),\ j = 1,..., p$ are unknown smooth functions satisfying the identifiability constraints

$$E\left[m\left(X_{itj}\right)\right] = 0,\ j = 1,..., p.$$

As a consequence, β represents the average effect, over the whole population, and the functions $m_j\left(.\right)$ indicates how the mean effect of the policy varies with the knowledge inputs.

In principle, equation (3) can be generalized by considering a non-additive specification by replacing (3) with a more general multivariate function

$$\beta_{it} = \beta + m\left(X_{it1},..., X_{itd}\right) \qquad (4)$$

For $2 \leq d \leq p$. Estimating (4) will allow for a greater flexibility at the price, because of the curse of dimensionality, of less precise estimates.

The rationale behind such a modelisation relies on the presence of absorptive capacity and non-neutral or even localized (to some specific inputs domain) inducement effects of environmental policy. Indeed, we could expect that environmental policy is transmitted to technological performances (green inventions in this case) with a significance and strength which depends on the country specific investments in knowledge. Ex-ante, it can be expected that the larger knowledge investments are, the stronger the possible role of policy in inducing new inventions. The higher the combination of any R&D/human capital sources, the stronger socio-technical system capacity to absorb the effect of the policy, translating this into inventions. Moreover, this may happen with possibly complex nonlinear shapes.

The economic system absorptive capacity is the ability to recognize the value of new external 'information', a policy in this case, assimilate it, and apply it to invention ends. Absorptive capacity can be regarded as an important factor in both corporate innovation and general competitive advantage (Duchec, 2017). The proposed specification is coherent with the evolutionary approach (Dosi, 1982) which stresses that "one-directional explanations of the innovative process, and in particular those assuming "the market" as the prime mover, are inadequate to explain the emergence of new technological paradigms". Policies are relevant, as many works have shown. This paper tries to scrutinise the extent to which the amount of public and private investments such as R&D, human capital and positive externalities like foreign R&D play a role in determining the magnitude of the policy effect.

4.3.2. Estimation results.

As far as the results are concerned, we adopt a general-to-specific modelling (Hendry et al., 2000), to select the variables to be considered to fit (3). This procedure leaded us to retain only two significant variables in (3): domestic and foreign R&D (RD and WRD). Using an approximate ANOVA test procedure (see Wood, 2017), an additive structure is strongly rejected in favour of a more general model based on bivariate regression functions:

$$\beta_{it} = \beta + m\left(RD_{it}, WRD_{it}\right)$$

Results indicate that the estimated average effect of the policy is positive with $\hat{\beta} = 0{,}15$ and it is significant in statistical terms (p-value=0.011). Thus, compared to the results in the previous section, allowing for a heterogeneous policy effect produces a higher estimated average effect and higher significance level.

As far as the estimated function $\hat{m}\left(RD_{it}, WRD_{it}\right)$ is concerned, Figure 6 draws the contour plot of the estimated bivariate function $\hat{m}\left(RD_{it}, WRD_{it}\right)$. It is worth recalling that the contours indicate the *varying* component of the policy effect, i.e. the effect of the policy that is varying nonparametrically with RD and WRD, $\hat{m}\left(RD_{it}, WRD_{it}\right)$, while the total estimated effect of the policy is given by $\hat{\beta}_{it} = 0{,}15 + \hat{m}\left(RD_{it}, WRD_{it}\right)$.

Overall, over all the domain of RD and WRD (Figure 6), it is found evidence that the effect of the policy nonlinearly and monotonically increases with both domestic and foreign R&D, pointing again to the joint relevance of internal and external knowledge towards the support of technological development through their joint effect with the policy. We can identify two macro regions.

A first macro region correspond to very low levels of internal/foreign R&D (Figure 7), where $\hat{m}\left(RD_{it}, WRD_{it}\right) < 0$, at the very extreme $\hat{m}\left(RD_{it}, WRD_{it}\right) \approx -0{,}5$, so that the total effect $\hat{\beta}_{it}$ is negative over a part of the analysed green knowledge generation domain. From an economic viewpoint, this points out a kind of 'coordination failure' or insufficient investments in the innovation drivers. At very low levels of these knowledge inputs, the costs outweigh the benefits. The absorptive capacity of the system, represented by the investments in knowledge, is insufficient to provide an effective framework where invention can arise through the inducement policy effect. From a statistical point of view, it can also be observed that for low levels of internal/foreign R&D, data are sparse and the estimates lack precision.

In the second, and most relevant, macro region, we observe $\hat{m}\left(RD_{it}, WRD_{it}\right) \geq 0$.This region corresponds to most part of the domain of RD and WRD. Specifically, it can be expected that environmental policies effects on innovation, need a critical amount of core investments in knowledge to exert the dynamic efficiency effects the theory prescripts (Porter and Esty, 1994; Milliman and Prince, 1989; Requate and Unhold, 2003) and indeed for average levels of internal/foreign R&D, we find that $\hat{m}\left(RD_{it}, WRD_{it}\right) \approx 0$ so that $\hat{\beta}_{it} \approx 0{,}15$ (Figure 8).

Then, by increasing the level of RD/WRD, threshold effects again matter, and are connected to some complementarity features of the underlying innovation function (Antonioli et al. 2013; Charlot et al, 2015). In fact, for high levels of internal/foreign R&D, the estimated function $\hat{m}\left(RD_{it}, WRD_{it}\right)$ turns to be positive and monotonically increases with both variables, up to a maximum where $\hat{m}\left(RD_{it}, WRD_{it}\right) \approx 1,5$ for extremely high levels, so that in that region of the domain, $0,15 \leq \hat{\beta}_{it} \leq 1,65$ (Figure 9).

Two main highlights of econometric and economic relevance arise. First, the results are clear-cut in showing how the effect of the policy nonlinearly and monotonically increases with both domestic and foreign R&D and more specifically suggesting that a critical mass of these inputs is necessary to make the policy effective. The proposed semiparametric model unveils heterogeneous policy effects, which operate through R&D layers, signaling that environmental policy effects on knowledge are significantly mediated by country investments in R&D. Domestic and foreign R&D act as knowledge absorptive capacity and enhances environmental policy effectiveness: the more the market and institutional environment is dense of R&D, the more the policy on air pollution is effective in driving green patents. Second, this evidence suggests that green patenting dynamics conceptually connects to two main relevant dimensions of a GKPF: (i) the complementarity of various invention drivers, here domestic and foreign R&D; (ii) the crucial role of R&D international spillovers, mediated by geographic distance, to directly contribute to green knowledge generation and in allowing the policy to become effective. Further studies may consider alternative transmission channels such as trade, technological proximity, language or genetic distance.

Figure 6– Heterogeneous policy effect: contour plot of $\hat{m}\left(RD_{it}, WRD_{it}\right)$

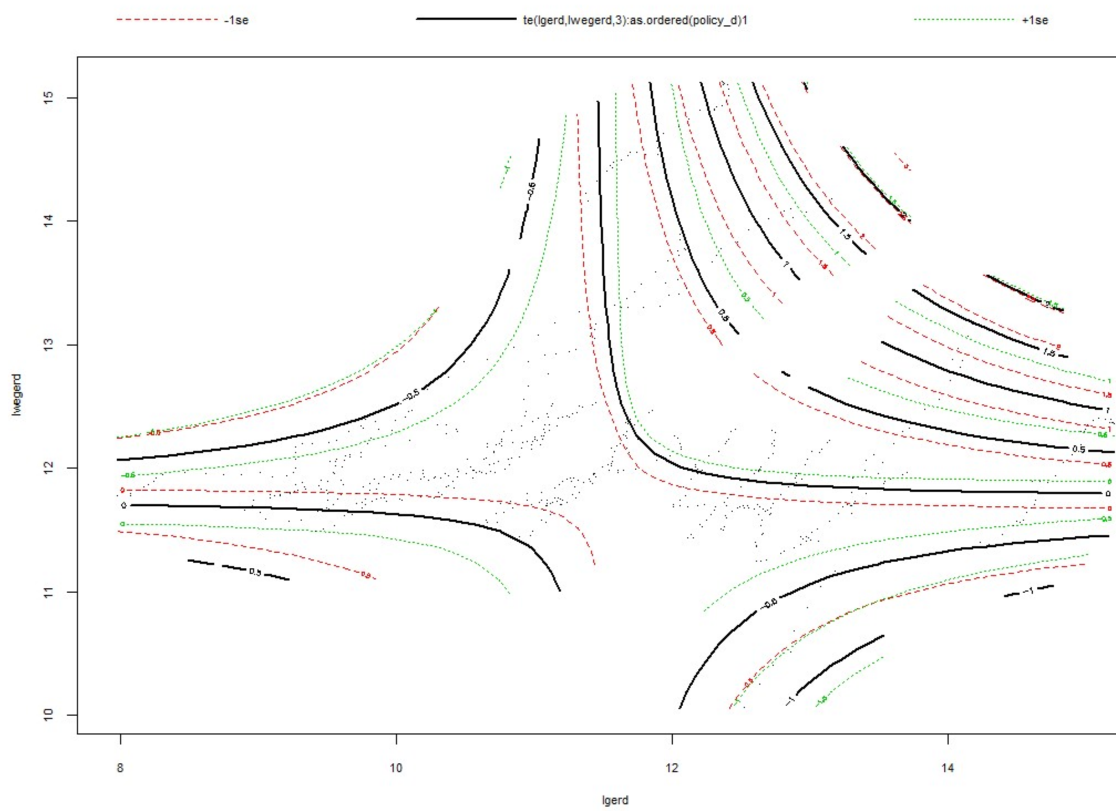
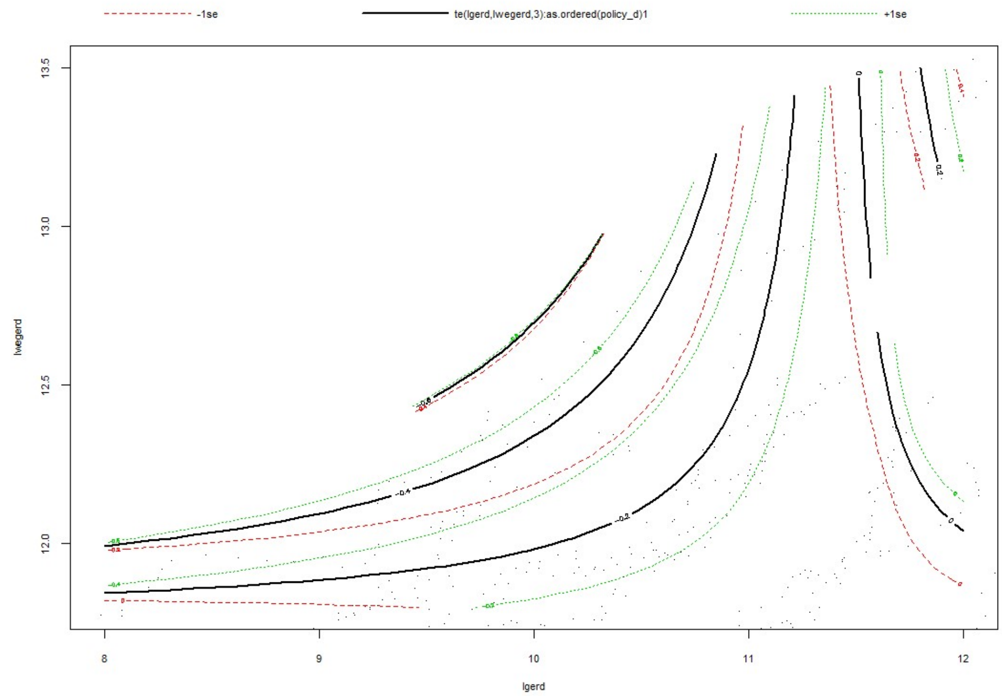


Figure 7– Heterogeneous policy effect: contour plot of $\hat{m}\left(RD_{it},WRD_{it}\right)$ for low levels of internal/foreign R&D: $\hat{m}\left(RD_{it},WRD_{it}\right)<0$



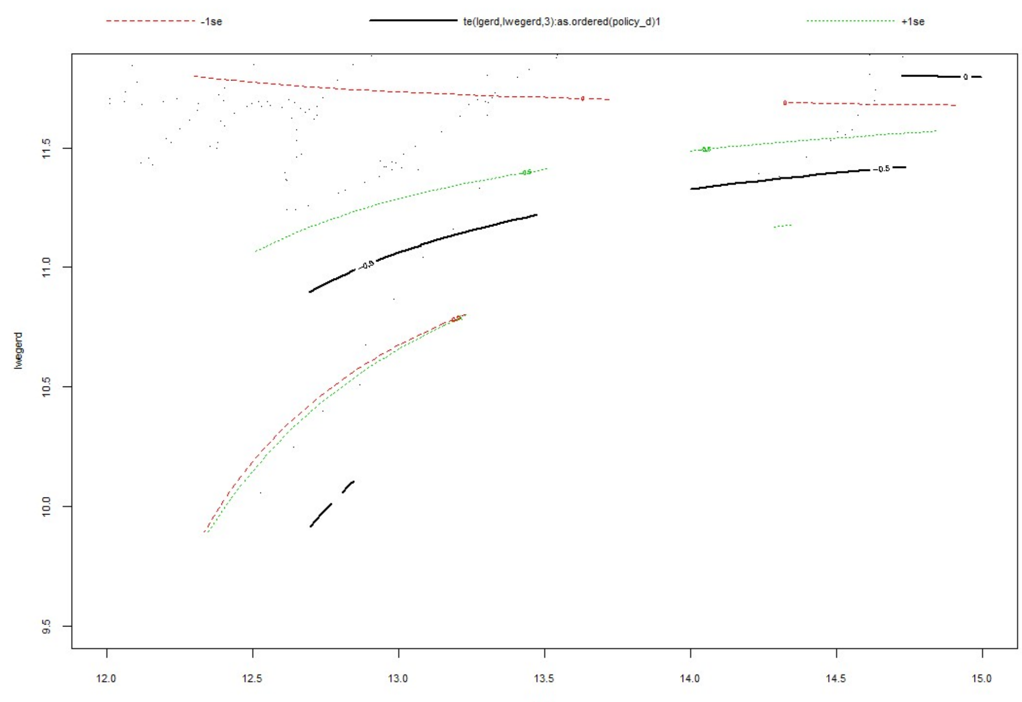


Figure 8 – Heterogeneous policy effect: contour plot of $\hat{m}(RD_{it},WRD_{it})$ for average levels of internal/foreign R&D: $\hat{m}(RD_{it},WRD_{it}) \square 0$ so that $\hat{\beta}_{it} \square 0{,}15$

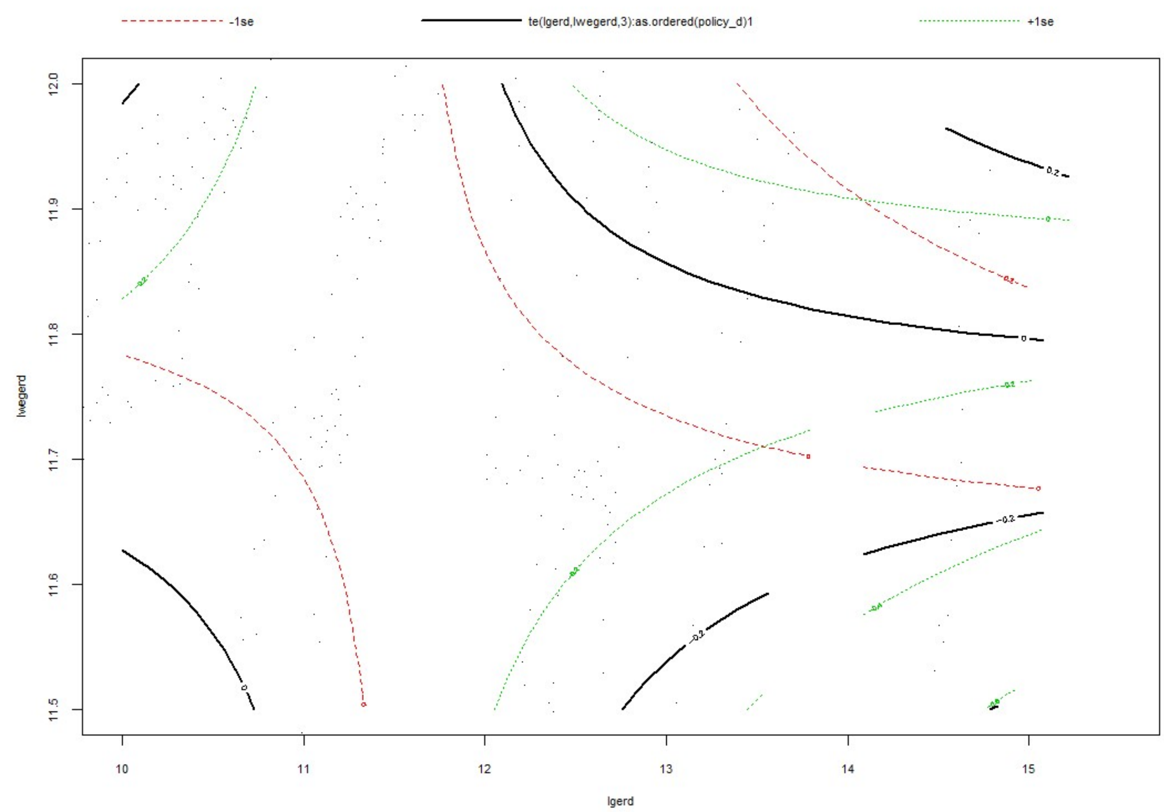
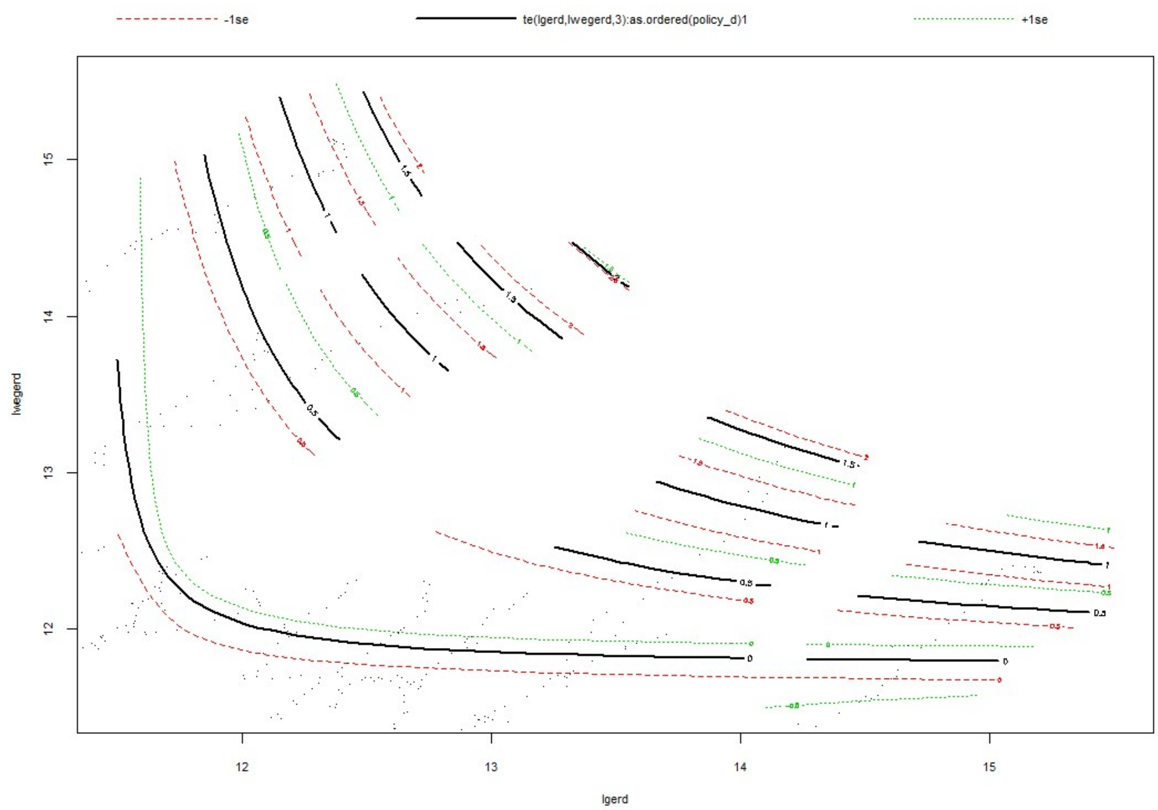


Figure 9 – Heterogeneous policy effect: contour plot of $\hat{m}(RD_{it}, WRD_{it})$ for high levels of internal/foreign R&D: $\hat{m}(RD_{it}, WRD_{it}) > 0$



4. Conclusions

The paper takes a macro-econometric long run perspective to examine Green Knowledge functions. The main methodological issues the investigation addresses are the possible *functional form bias* and *correlated unobservable factors* bias that may arise when adopting standard parametric fixed effects approaches. As a consequence, the work has considered semiparametric panel specifications with interactive fixed effects. The modelling framework the paper developed aims at enhancing the understanding of long-run innovation phenomena and setting flexible and sound policy assessment tools. With this regard, we consider a flexible specification that allows relaxing the hypothesis of homogeneous policy effects, considering effects that non-parametrically interact with the set of knowledge inputs, such as R&D and human capital.

In summary, the proposed semiparametric framework convey evidence on the existence of relevant nonlinearities, threshold effects and complementarities.

A first relevant result is that the effect of R&D, Human Capital and foreign R&D is characterised by relevant nonlinearities and thresholds. The specifications that emerge out of model selection reinforce the idea that non linearities and thresholds are relevant components of knowledge accumulation.

Environmental policies have significantly driven green inventions since the early 80's. The effect is significant from economic and statistical point of views. It is found that in order to unveil the significance and the endogeneity of the policy factor, non-parametric modelling is necessary. In fact, only non-parametric specifications allow disentangling average and cross country heterogeneous policy effects and drawing the relationships that exits between environmental policies on the one hand and R&D on the other hand. Following a sort of complementarity, in the flexible non parametric environment, estimates show that only if a country R&D investment and foreign R&D are jointly sufficiently high, then policies exert positive stimulus to innovation. Thresholds are revealed. In certain spaces of the innovation set, environmental policies can even be associated with a negative effect on green patenting if the stock of a country R&D is low.

The emergence of a potential and substantial complementarity connects a methodological issue (the heterogeneous policy effect) with a real world policy issue (the necessary R&D investments towards green technological development). The economic meaning is that those countries with too much low levels of domestic and foreign R&D are not providing a favourable setting for substantial policy inducement effects to appear.

Further analyses could consider extending the coverage to other policy domains, introducing non-binary policy index structures, comparing the KPF for green and non-green inventions, and considering other spillovers transmission channels.

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