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Abstract

Innovation is a primary engine of sustainable growth. This paper provides a new semiparametric econometric policy evaluation framework and estimates a green knowledge production function for a large, 30-year panel dataset of high-income countries. Because of the high degree of uncertainty surrounding the data-generating process and the likely presence of nonlinearities and latent common factors, the paper considers semiparametric panel specifications that extend interactive fixed effects fully parametric models such as the multifactor error model and the random trend model. It also 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 is the preferred model, (2) threshold effects and nonlinearities are relevant features of the data that are obscured in parametric specifications, and (3) the effect of environmental policy is significant and clearly heterogeneous when modeled as a nonparametric function of certain knowledge inputs. The evidence shows a relevant nonlinear policy inducement effect occurring through R&D investments.

Keywords: *green knowledge generation, environmental policy, heterogeneous policy effect, large panels, interactive fixed effects, spline functions, model selection.*

JEL: *C14, C23, C52, O3.*

1. Introduction

Economic and environmental sustainability is largely driven by technological and policy patterns (EEA, 2020). The achievement of a decarbonized, 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 economies (EEA, 2014). The major technological drivers of this age and the past three decades are the intensification of information and communications technologies, the rise of the Internet of Things, and the development of automation and robotics. The techno-organizational development of the green economy can be seen as another innovative step in *'shifting outward the production possibilities frontier for some generalised aggregate of potential human wants'* (Griliches, 1990, p.1669), where both smooth changes and discontinuities are present and where market- and policy-oriented explanations of the innovative process are necessary. Indeed, the green economy trajectory is characterized as a new sociotechnical paradigm with some incremental patterns and some strong discontinuities that depend on policy developments since the 1970s-1990s, when milestone conventions were inaugurated and the first policies were established (e.g., the US Clean Air Acts, the 1987 UN Convention on Sustainable Development, the 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. Environmental policy-induced technological progress (Milliman and Prince, 1989) is referenced in the history of environmental policy and international agreements. Starting with the Kyoto Protocol milestone, which refers 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'*, these agreements created expectations of more stringent targets favoring invention and innovation and, through the Clean Development and Joint Implementation Flexible Mechanisms, generated a market for international exchanges of technologies and related spillovers (Johnstone et al. 2010; Dechelezpretre et al. 2011). Within this overall context, the role of green technologies aimed at advancing the technology and sustainability transition needs to be investigated from a medium-long run perspective in connection with the evolution of policy.

With the increasing process of globalization, global factors, in addition to country-specific policies, may produce significant and possibly heterogeneous effects on countries' green innovation activities. For instance, crises of various kinds may greatly affect technological development, and economic crises, specifically, may produce market destruction and creation effects. Within the specific realm of the green economy, a milestone global event was COP21, held in Paris in 2015, which emphasized the role of innovation, with a focus on radical technological solutions for clean energy and the expansion of R&D expenditures aimed at boosting green innovations. In December 2019, the EU launched the European Green Deal, a set of 'measures accompanied with an initial roadmap of key policies [that] 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'. These global events yield heterogeneous innovation responses across countries.

On the basis of the aforementioned general framework, econometric models should represent in a meaningful and flexible way the complexity of green knowledge generation. Nonlinear dynamics, global factors, and environmental policies, among other things, are all cornerstones for a full understanding of the process of green knowledge generation. More specifically, it is worth studying whether and how innovation inputs produce nonlinear effects on green inventions, whether and how unobserved factors additionally affect the way knowledge is produced, and in this framework, whether and how environmental 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 factor* bias that may arise with the adoption of standard parametric fixed effects approaches. To do so, the paper considers semiparametric panel specifications, which 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 also been shown to be useful for policy evaluation (Fujiki and Hsiao, 2015; Wooldridge, 2005) and, more generally, to address endogeneity problems in a variety of empirical frameworks such as the Knowledge Production Function (KPF) and the output production function at different levels of aggregation (Charlot et al., 2015; Brown et al., 2006).

A specific focus of this paper is to assess the effect of environmental policy on green inventions. In so doing, while a common practice in the policy evaluation literature consists of focusing attention on the mean effect or imposing a homogeneous effect across units, as depicted by Cardot and Musolesi (2020), we also consider a model in which the effect of the policy is expanded as a nonparametric function of some key covariates (innovation inputs) 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 modelization lies in 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 performance with a significance and strength that depends on country-specific investments in knowledge-driving factors.

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

The model also allows for cross-sectional dependence, which is introduced as a result of a finite number of unobservable common factors that may have different effects on knowledge creation across countries.

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; Ma et al., 2015), this 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 investigations are:

- Assessing the functional form of green knowledge generation by focusing attention on model uncertainty, nonlinearities and unobserved common factors.
- Analyzing heterogeneous policy effects behind the GKPF.

Regarding environmental policies, we exploit official OECD sources. The policy dataset, with indicators constructed on the basis of raw OECD data, is longer in the time dimension than the OECD EPS policy indicator (Albrizio et al. 2017), which does not cover the 1980s. Although energy prices might be a sound proxy for 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 us to assess the threshold effects that strongly characterize the dynamic efficiency effects of policies. Energy prices, as a measure of policy, also capture market distortions related to the energy market and endowments of fossil fuels. It is often difficult to find the desired policy indicator due to data availability. For example, Acemoglu et al. (2016) use fuel prices (including energy taxes) to mimic and test the innovation inducement effect of a carbon tax.

The paper is organized as follows. Section 2 summarizes 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 the estimation. Section 5 extends the model by allowing for heterogeneous policy effects within a nonparametric and flexible approach. Section 6 concludes and provides suggestions for further research.

2. Related literature

The paper aims at connecting two literatures: the literature on the KPF, which was inspired by Griliches (1990), and the one studying green inventions and environmental policy, namely the policy induced innovation effect (Popp, 2002, 2019). Through the integration, the works aims at enhancing the analysis of green inventions and policy assessments.

As far as the KPF is concerned, most of the previous work focused on firm or on regional level of aggregation using cross-sectional or short panel data while, to the best of our knowledge, very few studies adopted a macroeconomic perspective over the long-run (see, e.g, Porter and Stern, 2000). On the side of environmental economics and policy, it complements and extends the green patents and green policy literature and in particular those papers that examine ‘directed technological change’ by studying clean technologies and policies with a focus on micro- and sector-based evidence. Among other seminal papers, the study by Acemoglu et al. (2016) analyzes the transition to a decarbonized economy through technology and estimates the model by using firm-level US energy sector data; the focus of the authors 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 dependence in clean technological innovations but also significant effects of a fuel tax, introduced as a proxy for carbon taxes. Other works have investigated firm’s innovative behavior, with special reference to the key specific EU emission trading policy setting, basically exploiting very detailed EU country based micro-datasets (Martin et al., 2014a; Calel, 2020), as well as works on the effects of a carbon tax on sector related innovations (Martin et al., 2014b). Specific environmental realms have been studied with respect to inventions, such as renewable energy fields (Nesta et al. 2014, Noailly and Smeets, 2015).

The paper thus takes a broader macroeconomic and longer-run perspective on the technological dynamics. This may provide new interesting insights to assess the historical role of policies, in strict integration with development drivers as R&D and human capital (spillovers) as a stimulus to green technologies for the transition to a non-fossil fuel economy (Heal, 2020, Perrons et al. 2020).

It specifically takes inspiration by Griliches (1990) and by recent papers on the field (Charlot et al., 2015) highlighting the complexity of knowledge generation and proposes the adoption of a new flexible modelling framework to study the relation between knowledge, which is best proxied by patents according to the Griliches framework, and its main drivers, namely R&D, human capital and also environmental policy. The modelling framework attempts to provide a new econometric modelling setting for studying green knowledge generation and assessing environmental policy effects, but its applicability goes well beyond energy and environmental economics.

Finally note that the present work focuses on a relevant set of high-income countries, given the goal of examining green knowledge generation and environmental policy dynamics over a 30-year period. Although the role of emerging and developing countries in producing green knowledge has increased over the past decades and technology transfers are crucial to achieving global sustainability, most innovation is still concentrated in a few more advanced countries that currently present a consolidated history regarding the evolution of environmental policy 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, data on green patents (GK) are collected from the OECD Stat databases. We consider patents that fall under the ‘selected environment-related technologies’ category as defined by the OECD (IPC: ENV_TECH) and that were granted by the USPTO (United States Patent & Trademark Office), and we calculate the number of patents country-wise according to the inventor or inventors’ country or countries of residence. Patents of an agent belonging to country i but submitted to country j are accounted for 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].

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 input factors. Specifically, we use gross domestic expenditure on research and development (GERD) flow values, collected from the OECD-Stats database, using total data as a source of funds. The data are in 2010 dollars – constant prices and PP. Missing values are filled in using a similar method to that of Coe et al. (2009), and then we calculate GERD

[1] Fractional counts are used 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. The patent family also captures the ‘quality’ of patents at the macroeconomic level.

stock values using the perpetual inventory method as in Coe and Helpman (1995), assuming the depreciation rate to be 0.05. The HK stock is collected from the Penn World Table version 9.0 (Feenstra et al., 2015).

To account for knowledge spillovers (see also Verdolini and Galeotti, 2011), we consider foreign RD and foreign HK (WRD and WHK, respectively). We use geographic proximity as a channel of technology diffusion because of 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), because 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 that incorporates the multidimensionality of policy efforts (OECD, 2016): deposit refund schemes, fees, tax rates of environmentally related taxes, tradable permits, voluntary approaches, and environmentally motivated subsidies (https://pinedatabase.oecd.org/). On the basis of these 6 categories, which are observed year by year and assume values of 0 or 1, a policy indicator assumes a value of 1 in the year of the introduction of a policy from one of the six categories. If several policies are introduced in a given year in the country, the indicator increases by one for each additional policy up to 6. The EP treatment variable 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, and energy efficiency, we focus in this paper on the domain of air pollution regulations (Berman and Bui, 2001), given the relatively longer history of air pollution policies over the considered period.

To address heterogeneous effects within a similar framework to that of Cardot and Musolesi (2020) but with the limitation in terms of sample size of using macroeconomic data, we decide to rely on a binary (0/1) treatment 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 characterize real-world innovation phenomena. The section outlines some time patterns and heterogeneous trends.

Figure 1 shows that the green patent pattern displays 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 (Australia, Canada, Denmark, Finland and Germany, to show diversified examples among others), they evolve on a rather linear trend, and finally, for a few other countries (South Korea, Portugal, Greece, Ireland, and Sweden[2]), they show a very deep increase after a period of stagnation. The observed patterns are coherent with a relatively earlier adoption of policies in more mature economies, which has produced a smoother evolution than that of some other countries that had lower income at the beginning of the environmental policy dynamics. The latter countries have substantially closed gaps in terms of both GDP and policy commitments as well. This is noteworthy since it shows that environmental policies with an international dimension in the realms of pollution and emissions can act as an additional lever of convergence through innovations.

[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. Fankhauser et al. (2013) present sector-based evidence on green patenting intensity in manufacturing, showing the top-placed countries (Germany, Japan) and significant heterogeneity among a set of high-income countries.

As far as the R&D stock is concerned, nonlinear increasing trends are also a feature of the data (Figure 2). It is worth mentioning that the achievement of an R&D/GDP ratio of 3% is one of the five headline targets of the Europe 2020 strategy for smart, sustainable, inclusive growth[3]. The EEA (2020) notes, "In 2017, [the] 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 extremely high cross-country heterogeneity in terms of R&D investments, the increase in the R&D stock from the beginning to the end of the period varies greatly across countries. While in Italy, it has grown by approximately 20%, in South Korea, it has increased by more than 200%.

Finally, when we look at the EP (air pollution policies) variable, overall, 45% of the observations are treated units. While the ex-ante logic of building this kind of policy variable is explained in the previous section, ex post, having two homogeneous groups in terms of size can be useful for estimating the model. Moreover, EP shows relevant variations in both the time and the cross-sectional dimensions (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% had implemented environmental policies by 2012. The OECD (2016) 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 the higher-income OECD counties (Finland, the Netherlands, Denmark) than for the lower-income OECD countries (Greece, Portugal, Ireland). Analogies with the aforementioned invention patterns are highlighted. The heterogeneity goes further anyway: due to diversified starting points and the 1995-2014 increases, some more mature countries in the EU and the Anglo-Saxon world, such as France, Italy, Australia, the UK, and the USA, are below the OECD average, while some initial laggards, such as Spain, Slovakia, Poland, and Korea, have moved up higher than the average (Botta and Kozluk, 2014).

Moreover, in view of estimating the model, we globally do not observe serious problems in terms of a lack of overlap. Observations that are out of support may affect the performance of regression approaches, mainly by affecting their precision (Lechner and Strittmatter, 2019). However, using flexible regression models, which are able to fit the data locally, is an effective way to address such a potential issue. *Nonlinearities*, *latent common factors* and possibly *heterogeneous policy effects* are all handled in the econometric framework presented in the next section.

FIG. 1-4 ABOUT HERE

3. Semiparametric modeling of green knowledge production and environmental policies

3.1 The modeling framework

The modeling framework is aimed at enhancing the understanding of long-run knowledge generation and setting new policy evaluation tools. As mentioned in the introduction, modeling the complexity of the knowledge generation is an important challenge of econometric analyses, 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 analyzing the link between policies and green innovations may produce additional insights for research in this field. To model the GKPF, we propose the following rather general semiparametric panel data model:

[3] Education and (clean) R&D investments are among the five policy items that can support the achievement of economic and climate goals, according to Hepburn et al. (2020), who also stress that green public infrastructure investments can drive down the cost of clean energy and start the 'green innovation machine'.

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

where GK_{it} measures green patenting activities, *g(.)* is a real unknown function, and RD_{it} and HK_{it} refer to the two main factors behind inventions, namely, R&D and human capital stocks[4]. WRD_{it} and WHK_{it} are introduced to take into account 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.

Note that the errors ν_{it} have a multifactor structure (Pesaran, 2006 and Su and Jin, 2012), with 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 modeled 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 that Charlot et al. (2015) adopt can be viewed as a special case of the multifactor error model (1). Obviously, by imposing homogeneous loading parameters, a common two-way fixed effect model is also obtained.

3.2 Econometric issues

The adopted econometric model specifically addresses the following issues: *Functional form and nonlinearities, Latent common factors and cross-sectional dependence, Endogeneity of the environmental policy variable and of the knowledge inputs, Model uncertainty*.

Functional form and nonlinearities. Although a log-log specification is customary in the literature on the KPF, the precise functional form cannot be straightforwardly defined on a theoretical basis, and alternative functional forms could better approximate the unknown functional relation. This relevant issue was recognized, 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. These considerations suggest that estimating a nonparametric relation between knowledge and its main inputs could be important to avoid a *functional form bias* (e.g. Charlot et al., 2015).

Latent common factors and cross-sectional dependence. The existing literature on the KPF has addressed the issues described above 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 motivation behind the use of the factor model lies in its ability to allow for 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, and global policies intended to raise the level of technology. The CCE approach by Pesaran (2006) explicitly allows for such cross-sectional dependence, which may pose inconsistency problems for standard estimation methods, and remains valid in a variety of situations that are likely to appear, such as the simultaneous presence of multifactor and spatial error structures and the existence of non-stationarity (Pesaran and Tosetti, 2011; Kapetanios et al., 2011). Note as well that also the two-way and the random trend

[4] It is here worth citing Griliches (1990, p.1674), who stresses that 'patents tend to be taken out relatively early in the life of a research project'. The empirical literature has noted that in the green realm, patenting activities arose quite early in the first environmental policy phases of the 1980s and 1990s (Jaffe et al. 1995; Jaffe and Palmer, 1997).

model allow for cross-sectional dependence arising from latent common factors, but with a lower degree of flexibility with respect to the multifactor error model.

Endogeneity of the environmental policy variable and of the knowledge inputs. A relevant issue to handle is the endogeneity of both the knowledge inputs and the policy variable. As far as the endogeneity of inputs is concerned, the existing literature motivated the issue due to the existence of omitted variables, which are likely to be correlated with R&D and/or human capital On the other hand the existence of reverse causality was discarded, as implied by the knowledge production function framework proposed by Griliches (1990, p. 1671) and suggesting a unidirectional link between patents and R&D. Another related issue is the possible existence of a link between current patents and past R&D spending. Employing an R&D variable that is built as a stock allows for such a link, while drastically reduces the curse of dimensionality problem; this is a common practice within the KPF literature. Similarly, as far as the policy dummy is concerned, it can be expected the existence of selection on both observable and unobservable (Heckman and Hotz, 1989), that is free correlation exists between the probability to be 'treated', and both observable and unobservable country-specific variables, such as institutional quality, cultural characteristics, etc. In order to implement the policy, countries may react to common agreements in a specific way, which could be related to country-specific and eventually unobservable characteristics.

As discussed by Wooldridge (2005), among others, the fixed effect approach is a powerful means of addressing such a kind of endogeneity problems; it has been largely employed in previous empirical studies on the determinants of patents. These studies generally employ the one-way or the two-ways model, allowing for individual and eventually time effects. However, the main limitation of the two-way model is that it imposes common time components that homogeneously affect all the countries, while most of unobserved factors are likely to heterogeneously affect different countries. With a specific focus on policy evaluation, the two-way model imposes that treated and non-treated statistical units would have followed a common trend in the absence of the policy, which is generally a too much restrictive assumption (Abadie 2005; Cardot and Musolesi, 2020).

For these reasons, adopting *interactive fixed effect models*, such as the random trend model or the factor model is a sound and robust framework for policy evaluation (Fujiki and Hsiao, 2015; Wooldridge, 2005; Heckman and Hotz, 1989) and, more generally, it is a relevant way to address endogeneity problems in the KPF and in a variety of other empirical frameworks, such as production, cost and wage function specifications (e.g., Wooldridge (2005), Bai (2009) and Saradis and Wansbeek (2012), who provide many examples that show how interactive fixed effects may be effective to address endogeneity problems). More specifically, the random trend model has been previously employed, among others, by Charlot et al. (2015) when modeling a regional KPF and by Brown et al. (2006) when assessing the effect of privatization policies on productivity within a neoclassical production function. Eberhardt et al. (2012) and Calderon et al. (2015) adopt a multifactor error model to estimate a production function, at a sectoral and at a country level, respectively.

It is worth noting in addition that the concept of causality used in macroeconometrics differs from that used in microeconometrics, as stressed by Lechner (2010); the endogeneity of input factors is generally handled in a different way when adopting firm level data. Indeed, while the typical way of modelling a KPF at firm level is considering the classical CDM framework (Crépon et al. 1998), the identification of a production function, which is a closely related framework, remains an intricate empirical matter when a researcher deals with firm's data.[5]

Model uncertainty. We recognize the existence of high uncertainty surrounding the true DGP. In general, there is a bias-efficiency trade-off when comparing parsimonious to complex models (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.

[5] In principle, the potential endogeneity of the input set (the so-called 'transmission bias') can be handled through, for instance, the adoption of structural identification approaches, that account for the fact that investment decisions may be affected by past productivity shocks (Olley and Pakes, 1996). At the same time, however, some recent and relevant works (Ackerberg et al., 2015; Gandhi et al., 2019) suggest that structural estimation methods may face identification problems, while, at the same time, transmission bias may not be so empirically important when estimating value added production functions: the OLS estimator itself can be performing pretty well (Ackerberg et al., 2007; Antonioli et al., 2020).

3.3 Estimation approach

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 within the (generalized) additive model's framework (Wood, 2020). Penalized regression splines combine the features of both regression splines, which use less knots than data points but do not penalize roughness, and smoothing splines, which control the smoothness of the fit through a penalty term but use all data points as knots. Moreover, while asymptotic results have recently been provided, they have been also proven to perform well empirically (see, e.g. Gioldasis et al. 2020).

We specifically employ thin plate regression splines, which are introduced by Wood (2003) and are optimal low rank eigen-approximation to thin plate splines. Thin plate splines are somehow ideal smoothers but are not computationally attractive because their computation require the estimation of as many parameters as the number of data points. Thin plate regression splines avoid the problem of knot placement that usually complicates modeling with splines and more generally have some optimality properties, while they also are computationally efficient. Finally, the smoothing parameter is selected by the restricted maximum likelihood (REML) estimation, which, relative to other approaches, is less likely to develop multiple minima or to undersmooth at finite sample sizes.[6]

4. Main results

4.1 Model selection: parametric and semiparametric specifications

Model selection is performed by applying recent advances in the field. It is well known that smooth model selection via marginal likelihood comparison is not valid and that a viable alternative is adopting an information criterion, such as the AIC (Akaike Information Criterion), based on the conditional likelihood of the model coefficients. Within the exponential family frameworks, Hastie and Tibshirani (1990) proposed a largely used conditional AIC in which the effective degrees of freedom of the model are used rather than the number of parameters. Subsequent studies (see, e.g. Reven and Kneib (2010)) showed that this approach tends to select too much complex models. Recently, Wood et al. (2016) proposed an AIC that overcomes such a problem and, more generally, that avoids to neglect the smoothing parameter uncertainty in the conditional AIC and that it is easy to compute. Wood (2020) provided further details and in particular, it gives useful insights to obtain a BIC (Bayesian Information Criterion) type, which is often preferred over AIC (Claeskens and Hjort, 2008).

Specifically, we consider the BIC (Wood et al., 2016; Wood, 2020) to 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), $v_{it} = \gamma_i' f_t + \varepsilon_{it}$; the random trend model including individual time trends (Wooldridge, 2005), $v_{it} = \gamma_i t + \varepsilon_{it}$; and time dummies (two-way fixed effects), $v_{it} = \lambda_t + \varepsilon_{it}$.

For the function g(.), we consider both parametric linear models and semiparametric additive models that avoid the curse-of-dimensionality problem of a fully nonparametric model, which was computationally unfeasible in our framework. In total, we consider six alternative models.

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

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

[6] Computations are performed within the R environment, and in particular, the semiparametric specifications are estimated by exploiting the mgcv package.

Overall, the results provide interesting insights into model selection. It is indeed found that the random trend specification always performs better than the two-way fixed effects model and the multifactor error model (CCE). This is an extremely interesting result suggesting the use of an intermediate level of heterogeneity for the modeling of unobserved common factors; the random trend model is 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 to be, ex post, an excessively restrictive assumption. Finally, note that in two cases out of the three (the random trend and the two-way model), the specification with additive smooth terms outperforms the parametric linear model.

Three main remarks are in order. First, note that the preferred model allows for an intermediate-high level of flexibility since it allows for smooth additive effects of the regressors along with individual trends. Both excessively simple models, such as the parametric or the two-way fixed effects models, and excessively complex specifications, such as the multifactor error, are thus rejected (see also Baltagi et al., 2002, 2003).

Second, it is worth noting that allowing for smooth additive terms and individual trends provides a more credible identification of the policy effect than that provided by parametric models and/or a standard two-way model (for a more detailed discussion, see, e.g., Cardot and Musolesi, 2020; Wooldridge, 2005; Lechner, 2010, 2015)

Third, as far as endogeneity is concerned, it is important to note that the random trend model identifies the parameters and functions of interest under a conditional strict exogeneity assumption (Wooldridge, 2005), such that

$$E\left(GK_{it} \mid X_{i1},...,X_{iT},c_i,\gamma_i\right) = E\left(GK_{it} \mid X_{it},c_i,\gamma_i\right),$$

for *t=1,…,T* and where X_{it} is the line vector of the explanatory variables, $X_{it} = \left(EP_{it}, RD_{it}, HK_{it}, WRD_{it}, WHK_{it}\right)$. Clearly such a conditional strict exogeneity assumption provides a more credible identification than the one arising from the individual fixed effects model (i.e. $E\left(GK_{it} \mid X_{i1},...,X_{iT},c_i\right) = E\left(GK_{it} \mid X_{it},c_i\right)$) and this because of two main reasons. First, it does not restrict the correlation between $\left(c_i,\gamma_i\right)$ and $\left(X_{i1},...,X_{iT}\right)$, thus taking into account the endogenous nature of the explanatory variables with respect to both time-invariant and time-varying correlated unobservable factors, where $\gamma_i t$ is broadly proxying this latter kind of unobservables (see also Heckman and Hotz, 1989). Second, it is quite natural to expect that the determinants of green patents, RD_{it} and HK_{it}, have the same deterministic component as for GK_{it}, so that they depend on both c_i and γ_i. Consequently, it is likely that shocks to green patents today may affect some innovation determinants in the future if individual trends are not controlled for, making the standard fixed effect estimator biased and inconsistent as the underlying strict exogeneity assumption will be violated.

In summary, the random trend model gives the best performances within the logic of an information criterion but also provides a much more credible identification than standard fixed effects models.

TABLE 1 ABOUT HERE

4.2 Estimation results

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

In this section, we focus attention on the results of estimating model (1). We mainly focus our attention on the functional relation between green patents and their main inputs, eventually highlighting possible nonlinearities and threshold effects.

The results concerning the additive nonparametric components of model (1) are presented in Figure 5. The three graphs depict the estimated univariate smooth functions for the inputs that are found to be statistically significant. We also computed the p-values for the smooth terms using Wald test statistics as suggested by Wood (2012). These are p-values associated with the Wald test of the hypothesis that the whole function equals zero. Low p-values indicate a low likelihood that the splines of the function are jointly zero. Additionally, note that smooths are subject to sum-to-zero identifiability constraints as detailed in Cardot and Musolesi (2020).

The estimated smooths (except WHK) appear to be highly significant, showing extremely low p-values on the Wald tests. Moreover, using an approximate ANOVA test procedure (Wood, 2017), linearity is always rejected for all explanatory variables except WHK. WHK instead presents a positive linear effect, which is not statistically significant (p-value=0.27). The non-significance of WHK is consistent with the literature focusing on international technology diffusion, which stresses the role of R&D spillovers (Ertur and Musolesi, 2017).

Additionally, note that the response and 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 as expected, the estimated smooth functions are highly nonlinear, with relevant threshold effects. Indeed, for all three significant variables (RD, HK, and WRD), a critical mass is necessary to ensure an effective impact on green patenting. This result is consistent with some related literature focusing on nongreen knowledge creation and/or different levels of aggregation (Varga, 2000, Charlot, 2015).[7] Evidence for RD and HK attests that policy targets on these inputs are justified to support innovation and growth, as the number of countries making substantial knowledge investments (e.g., 3% of GDP or higher) enhances the spillover effect. Countries that have structurally invested in R&D over the last decades, such as Japan, the USA, Germany, South Korea, and China, as well as Denmark and Sweden on a relatively smaller scale, present large shares of top inventions in climate-related technologies. The ascending phase of the climate change patent trend was around the mid-1990s, influenced by new policy expectations (Dechelezpretre et al. 2009). Nevertheless, investing in R&D matters if substantial thresholds are structurally surpassed. It is worth noting that the R&D/human capital and policy factors could be entangled. The fact that the mid-1990s witnessed a turning point in R&D-intense countries that proactively responded to new policies is a signal of an interconnection: to induce inventions, policies need a preexistent, dense R&D environment. Section 4.3 below focuses on the analysis of interactive policy effects to shed further light. Spillovers are the other key component of technological inducement. In the specific framework of green energy knowledge development, Verdolini and Galeotti's (2011) panel data analysis demonstrates 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'.

As for the effect of the policy, which is assumed here to be constant both across countries and over time, the parameter β, which also identifies the average treatment effect, is estimated to be 0.01 and is almost significant at the 5% level (p-value=0.055). This result thus indicates a positive effect, albeit small in magnitude[8]. Provided that the dependent variable is logarithmic, the estimated policy effect - which is a

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[7] It is worth noting that the 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 in which the plots cannot be easily interpreted correspond to low levels of HK and to very low levels of RD and WRD.

[8] Jaffe and Palmer (2001) find little evidence of effects on innovative outputs using regulation compliance costs as a proxy for policies in a panel of US manufacturing industries. Brunnermier and Cohen (2003) find mixed evidence on the effects of environmental regulations on environmental innovations proxied by patents for a panel of US industries.

homogeneous shift in the regression function - represents the percentage change in the predicted GK when EP=1 versus when EP=0, holding the other factors constant.[9]

What we do substantially find through this analysis is that over the time span that embraces the second US Clean Air Act, the Rio Convention, the Kyoto Protocol and the EU 2020 climate and energy package, all key examples of policy steps of international relevance, a high level of policy intensity brought about specific effects on green inventions. This outcome enriches the macroeconomic evidence on policy effectiveness that, among others, Johnstone et al. (2010, 2012) provide, first over a similarly long time span (1978-2003), but focusing on renewable energy policies, and then over a more restricted time span and using opinion survey-based policy indicators. McKitrick (2007), who takes a long-run perspective and specifically focuses on air pollution trends, finds that more than oil price effects, the 1970 Clean Air Act, a milestone policy to abate air pollution, was a relevant structural factor that induced accelerated abatement technologies.

In summary, the estimation of a *semiparametric random trend model* indicates that the long-run evolution of green inventions was indeed affected by environmental policy and mostly 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, at least in the present time span, no influence on green inventions.

4.2.2 A comparison with a misspecified parametric model

It is interesting to compare these results with those that 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 comparison.

Specifically, when we estimate a traditional parametric random trend model, i) the policy effect decreases substantially and becomes negative, with $\hat{\beta} = -0.0015$, and is no longer statistically significant (p-value=0.97); ii) among the domestic knowledge inputs, only RD is significant at standard levels, with an estimated elasticity of 0.47 (p-value=1.62e-05), while the human capital stock has a positive effect (0.057) but is not significant (p-value=0.98); and iii) the estimated coefficients associated with WRD and WHK both have 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 is found, for instance, in Cardot and Musolesi (2020). These estimates also suggest that adopting a flexible specification permits more credible and refined results with respect to the effect of continuous knowledge inputs, since nonlinearities and thresholds are important features of knowledge generation. Estimating a traditional parametric model would have produced a substantial *functional form bias*.

FIG. 5 ABOUT HERE

4.3 Extending the model: interactive policy effects

4.3.1. Econometric modeling

Common practices in policy evaluation consist of focusing attention on the mean effect of a policy or imposing a homogeneous effect across units and overtime, as we did in the previous section. Adopting model (2) was extremely useful because it allowed us to i) conduct a direct comparison with parametric models (see subsection 4.2.2) and ii) focus attention on the functional relation between patents and knowledge inputs.

In this section, we focus on the effect of the policy and specifically search for possible heterogeneous policy effects by exploiting the modularity and flexibility of spline modeling. Following Cardot and Musolesi (2020),

[9] More formally, this percentage difference is given by $100 * \left[\exp\left(\hat{\beta}\right) - 1\right]$.

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. Put differently, environmental policy nonparametrically interacts with some continuous covariates: in doing so, the discrete policy produces not only a neutral shift but also a more general change in the estimated nonparametric functions. 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, 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 $m_j\left(.\right)$ indicate how the mean effect of the policy varies with the knowledge inputs.

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

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

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

The rationale behind such a modelization lies in the presence of absorptive capacity and non-neutral or even localized (to some specific input domain) inducement effects of environmental policy. Indeed, we can expect that environmental policy is transmitted to technological performance (green inventions, in this case) with a significance and strength that depend on the country-specific investments in knowledge-driving factors, which become types of 'innovation endowments' (see also Jaffe et al. 1995; Jaffe et al. 2002).

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 is the sociotechnical 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's absorptive capacity is the ability to recognize the value of new external 'information', a policy in this case, assimilate it, and apply it to the ends of invention. Absorptive capacity can be regarded as an important factor for general competitive advantages, as in Dosi (1982), who 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 scrutinize the extent to which the amount of public and private investments such as R&D, human capital and positive externalities such as 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 backward selection procedure (Cardot and Musolesi, 2020) to select the variables to be considered to fit model (3). This procedure leads us to retain only two significant variables in model (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 favor of a more general model based on bivariate regression functions:

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

The results indicate that the estimated average effect of the policy is positive and sizeable, with $\hat{\beta} = 0.15$, and 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 for the estimated function $\hat{m}\left(RD_{it}, WRD_{it}\right)$, 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 varies 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 the whole domain of RD and WRD (Figure 6), there is 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 for the support of technological development through their joint effect with the policy. We can identify two macro regions, which are described below.

The first macro region corresponds to very low levels of internal/foreign R&D (Figure 7), where $\hat{m}\left(RD_{it}, WRD_{it}\right) < 0$, and 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 part of the analyzed green knowledge generation domain. From an economic viewpoint, this points to a kind of coordination failure or insufficient investment 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 effect of the policy. From a statistical point of view, it can also be observed that for low levels of internal/foreign R&D, the 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 of the domain of RD and WRD. Specifically, it can be expected that environmental policies' effects on innovation require a critical amount of core investments in knowledge to exert the dynamic efficiency effects that theory predicts (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, we find that threshold effects again matter and are likely connected to some complementarity with the underlying innovation function (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 positive and monotonically increases with both variables, up to a maximum at which $\hat{m}\left(RD_{it}, WRD_{it}\right) \cong 1.5$, 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, suggesting, more specifically, that a critical mass of these inputs is necessary to make the policy effective. The proposed semiparametric model reveals heterogeneous policy effects, which operate through R&D layers, signaling that the effects of environmental policy on knowledge are significantly mediated by country investments in R&D. Domestic and foreign R&D act as knowledge absorptive capacity factors and enhance the effectiveness of environmental policy effectiveness: the denser the market and institutional environment is in R&D, the more effective the air pollution policy is in driving green patents. Second, this evidence suggests that green patenting dynamics conceptually connect to two main relevant dimensions of a GKPF: (i) the complementarity of various invention drivers, here domestic and foreign R&D, and (ii) the crucial role of R&D spillovers, mediated by geographic distance, in directly contributing to green knowledge generation and allowing the policy to become effective. Further studies may consider alternative transmission channels such as trade, technological proximity, language or genetic distance.

FIG. 6-9 ABOUT HERE

4. Conclusion

The paper takes a macroeconometric long-run perspective to examine green knowledge production functions. The main methodological issues the investigation addresses are the possible *functional form bias* and *correlated unobservable factor* bias that may arise when adopting standard parametric fixed effects approaches. As a consequence, the work has considered semiparametric panel data specifications with interactive fixed effects. The modeling framework that the paper developed also aims at enhancing the understanding of long-run innovation phenomena and the setting of flexible and sound policy assessment tools. In this regard, we consider a flexible specification that allows us to relax the hypothesis of homogeneous policy effects, considering effects that non-parametrically interact with some knowledge inputs, such as research activity.

A first relevant result is that the effects of R&D, human capital and foreign R&D are characterized by relevant nonlinearities and thresholds. The specifications that emerge from the model selection reinforce the idea that nonlinearities and thresholds are relevant components of knowledge creation in the specific case of green innovation activities.

Another important result is that environmental policies have significantly driven green inventions since the early 1980s. The effect is significant from both an economic and a statistical point of view. It is specifically found that to fully unveil the significance and strength of environmental policy, allowing for heterogeneous/interactive policy effects is necessary. In fact, the consideration of a model in which the effect of policy is expanded as a nonparametric function of some knowledge inputs indicates that the estimated induced policy effect, which is mediated by domestic and foreign R&D, is on average positive and highly significant. It is also found that such an effect nonlinearly increases with both domestic and foreign R&D and that a critical mass of both variables is necessary to make the policy effective. Threshold effects are again relevant, as at extremely low levels of R&D activity, environmental policy may even produce a negative effect on green patenting. The emergence of a substantial complementarity between innovation policies and R&D activity connects a methodological issue (the heterogeneous policy effect) with a real-world policy issue (the necessary R&D investments for green technological development). The economic meaning is that those countries with excessively low levels of domestic and foreign R&D are not providing a favorable setting for substantial policy inducement effects to appear.

In summary, the proposed semiparametric framework offers evidence on the existence of relevant nonlinearities, threshold effects and complementarities. It points out the need for a critical mass of knowledge inputs to sustain technological development through a direct effect of these inputs on knowledge creation but also via an induced policy effect occurring through R&D activity.

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 spillover transmission channels.

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FIGURES AND TABLES

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

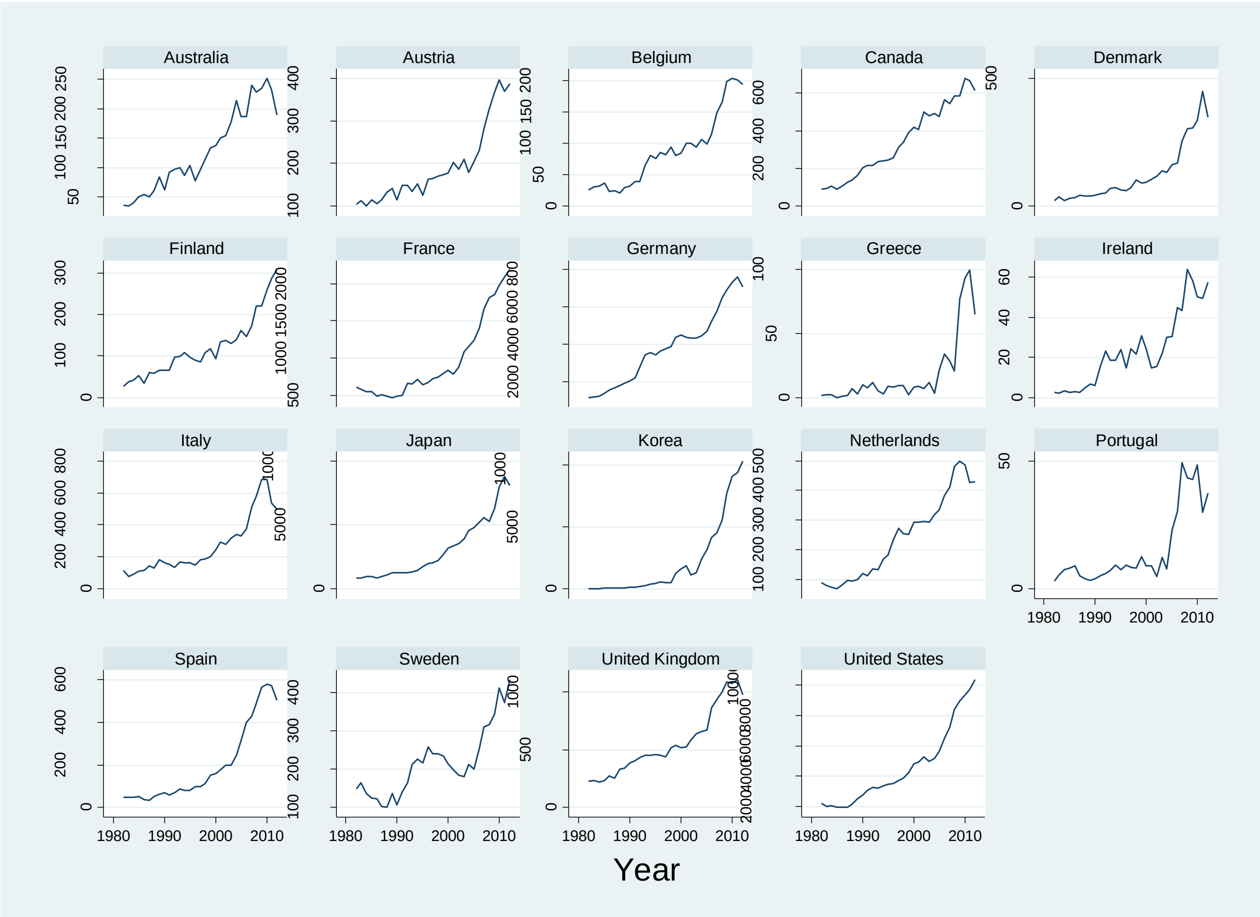
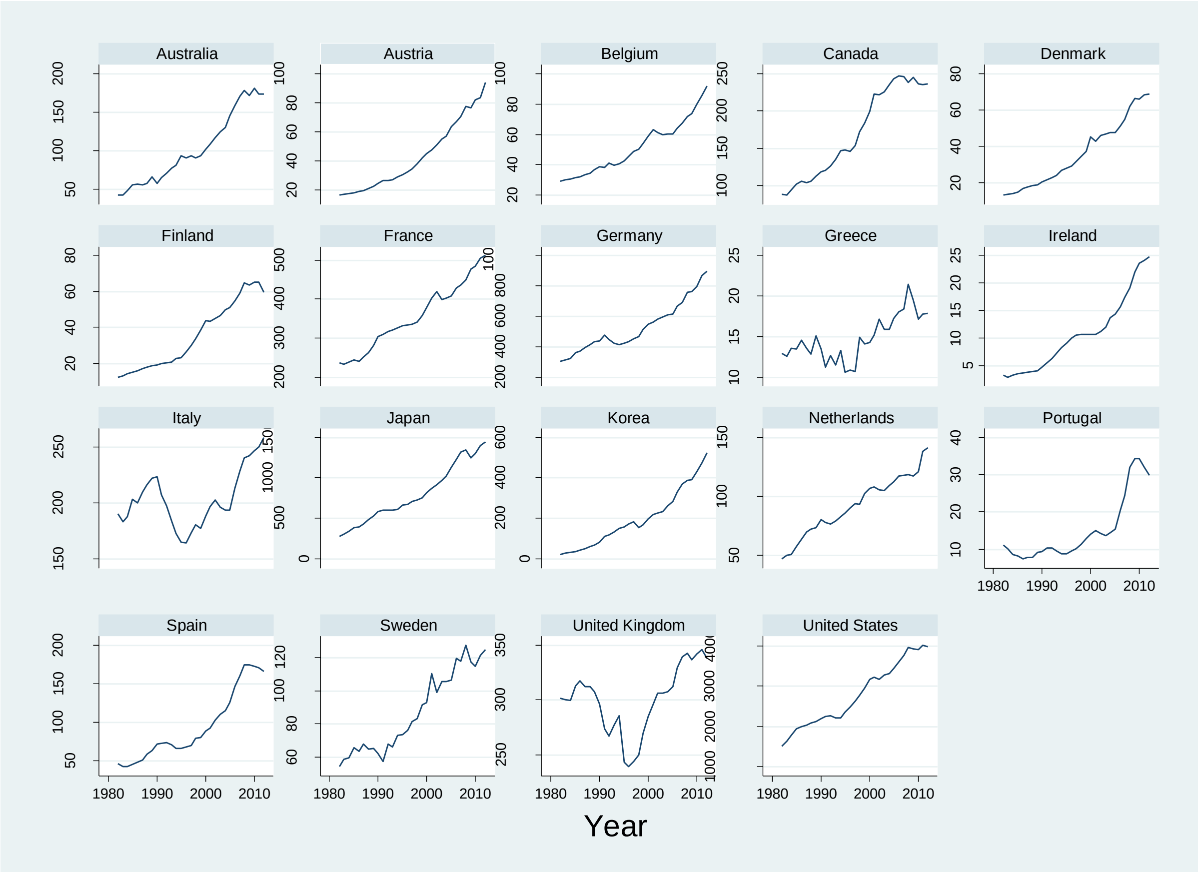


Figure 2 – Trends in R&D stocks (public and private R&D)



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

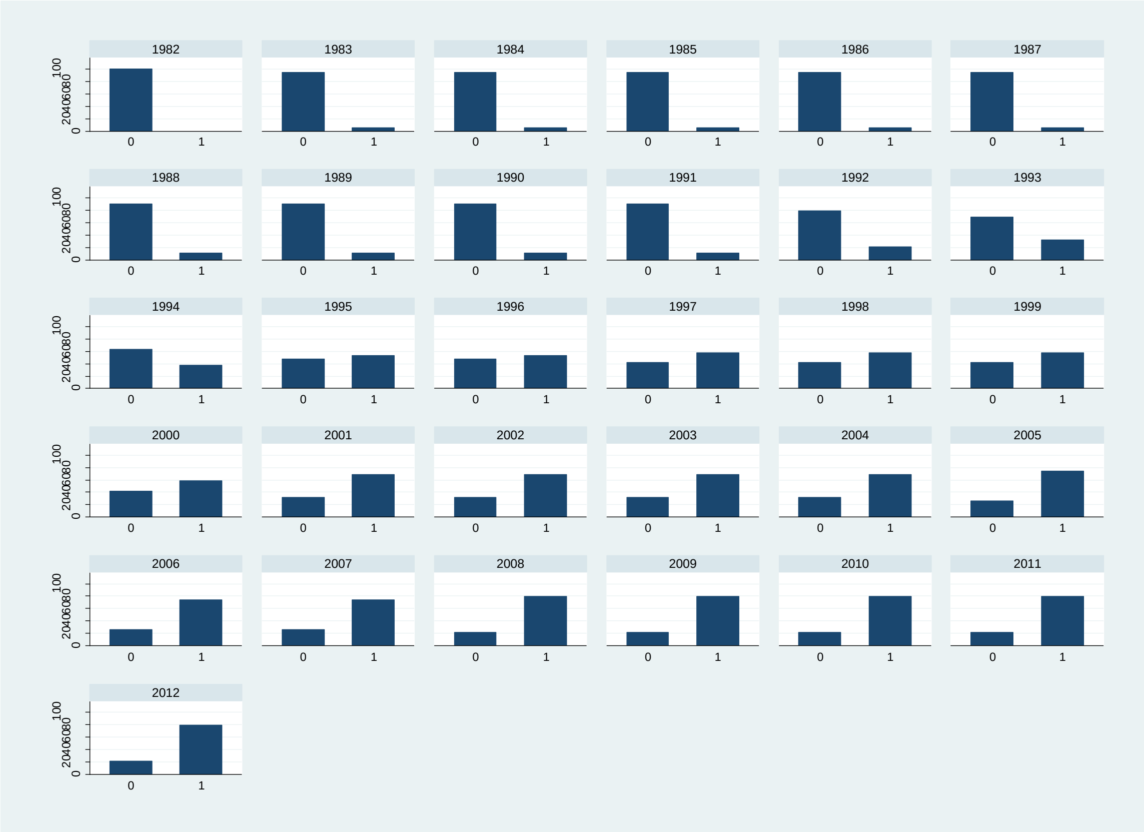


Figure 5 – R&D (a), human capital (b) and RD spillover (c) effects on green inventions: estimated univariate smooth functions

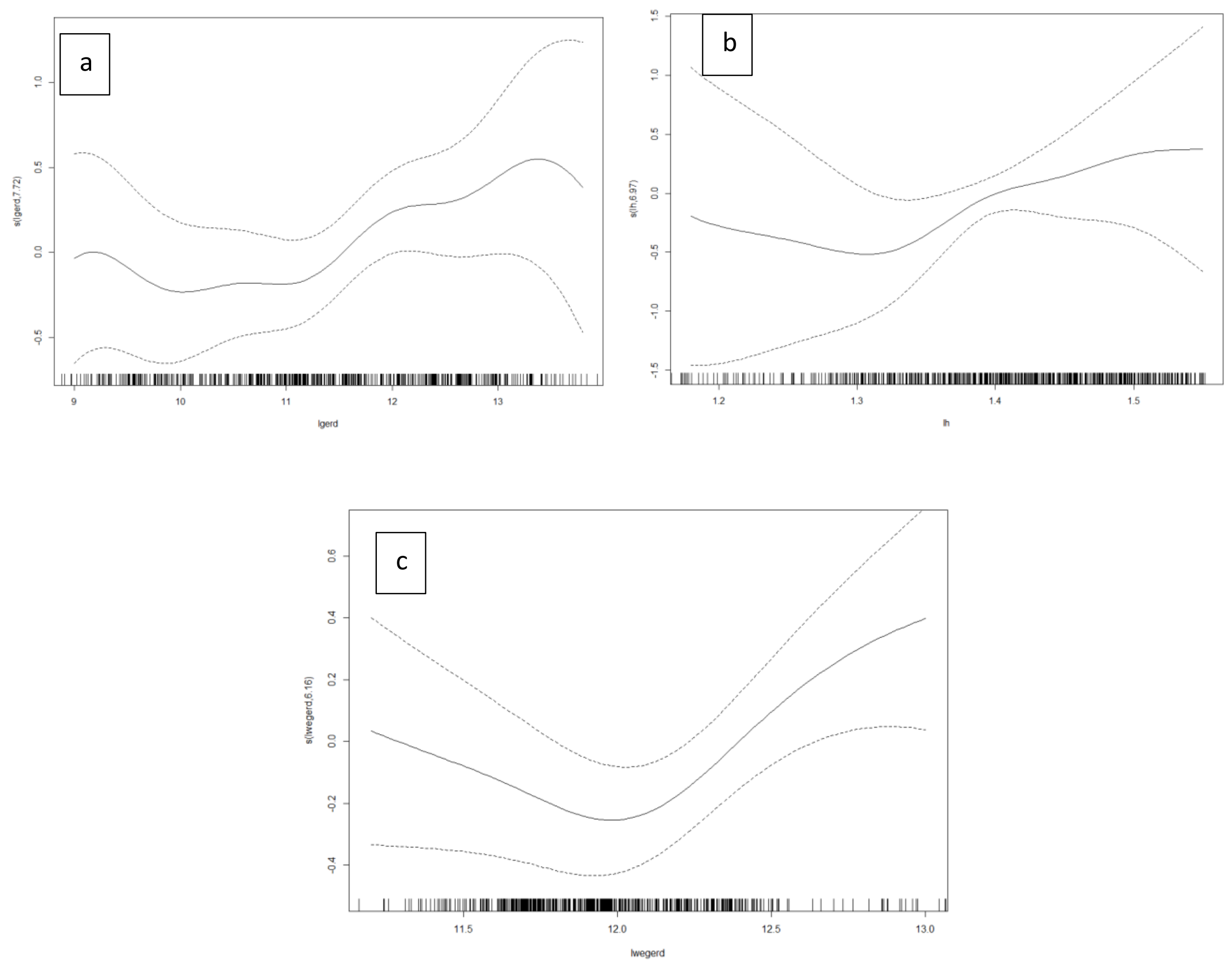


Figure 6 – Heterogeneous policy effect: contour plot of $\hat{m}(RD_{it}, WRD_{it})$

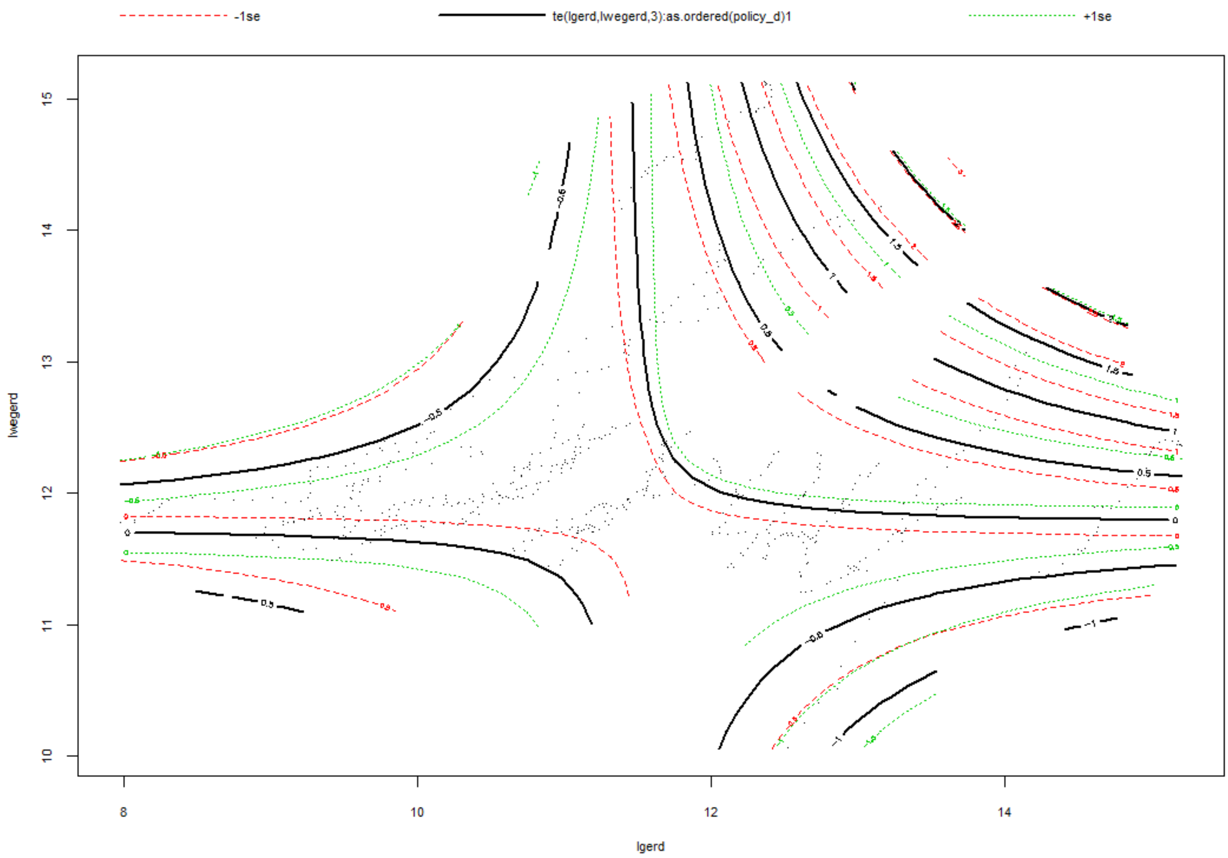
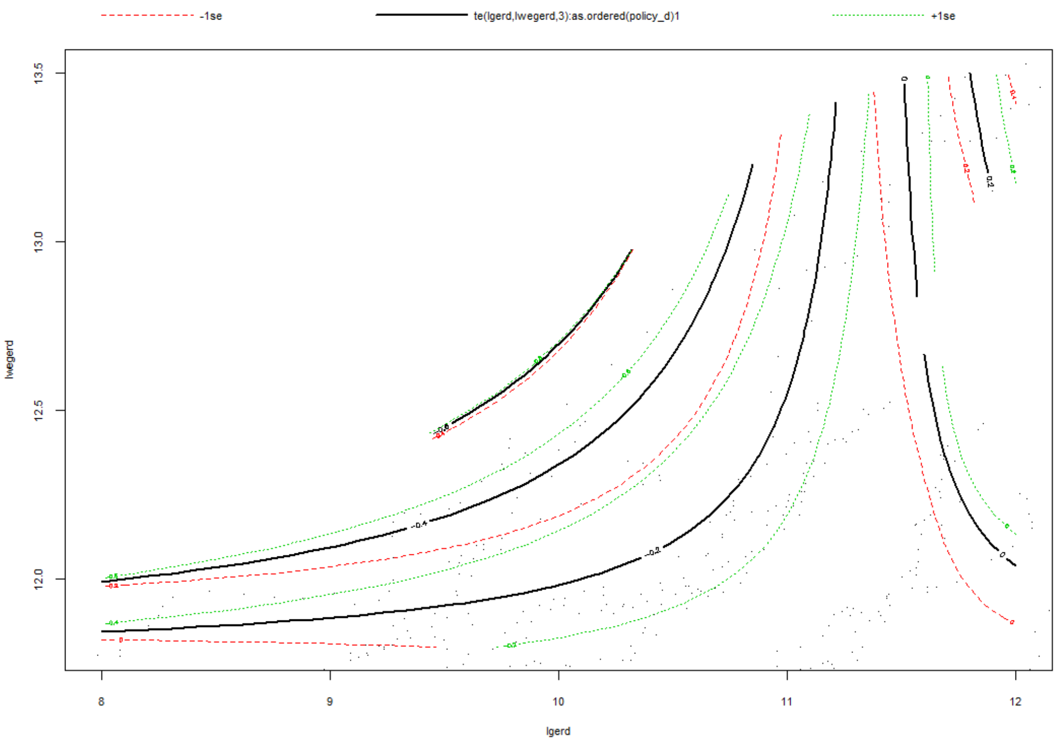


Figure 7– Heterogeneous policy effect: contour plot of $\hat{m}\left(RD_{it}, WRD_{it}\right)$ **for low levels of internal/foreign R&D,** $\hat{m}\left(RD_{it}, WRD_{it}\right) < 0$



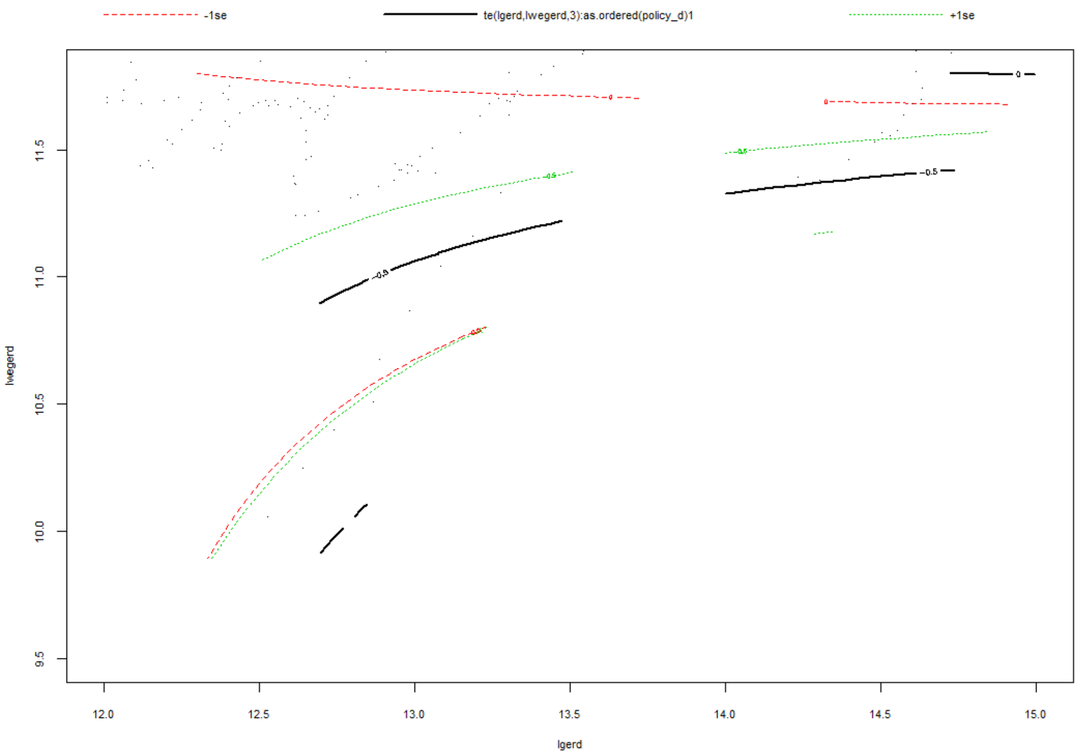


Figure 8 – Heterogeneous policy effect: contour plot of $\hat{m}(RD_{it}, WRD_{it})$ for average levels of internal/foreign R&D, $\hat{m}(RD_{it}, WRD_{it})$ □ 0, so that $\hat{\beta}_{it}$ □ $0{,}15$

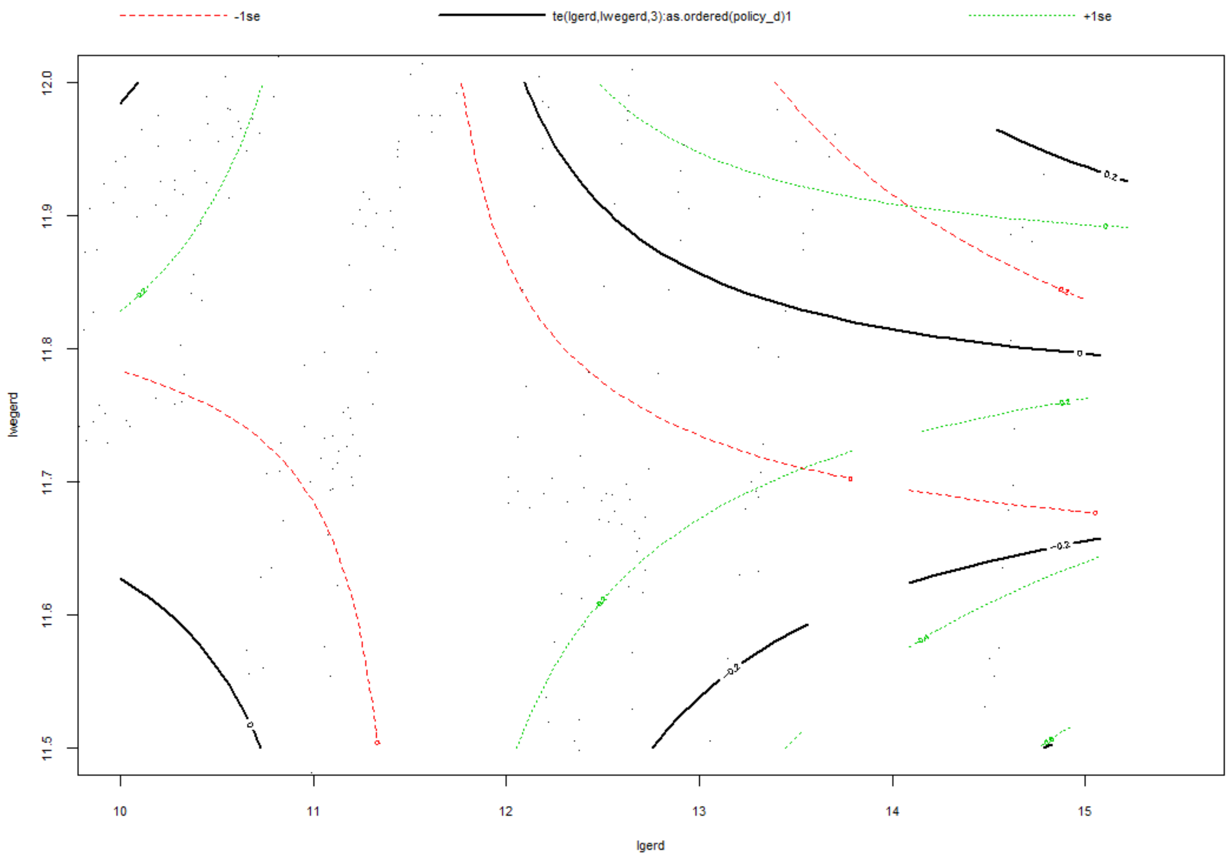


Figure 9 – Heterogeneous policy effect: contour plot of $\hat{m}(RD_{it}, WRD_{it})$ for high levels of internal/foreign R&D, $\hat{m}(RD_{it}, WRD_{it}) > 0$

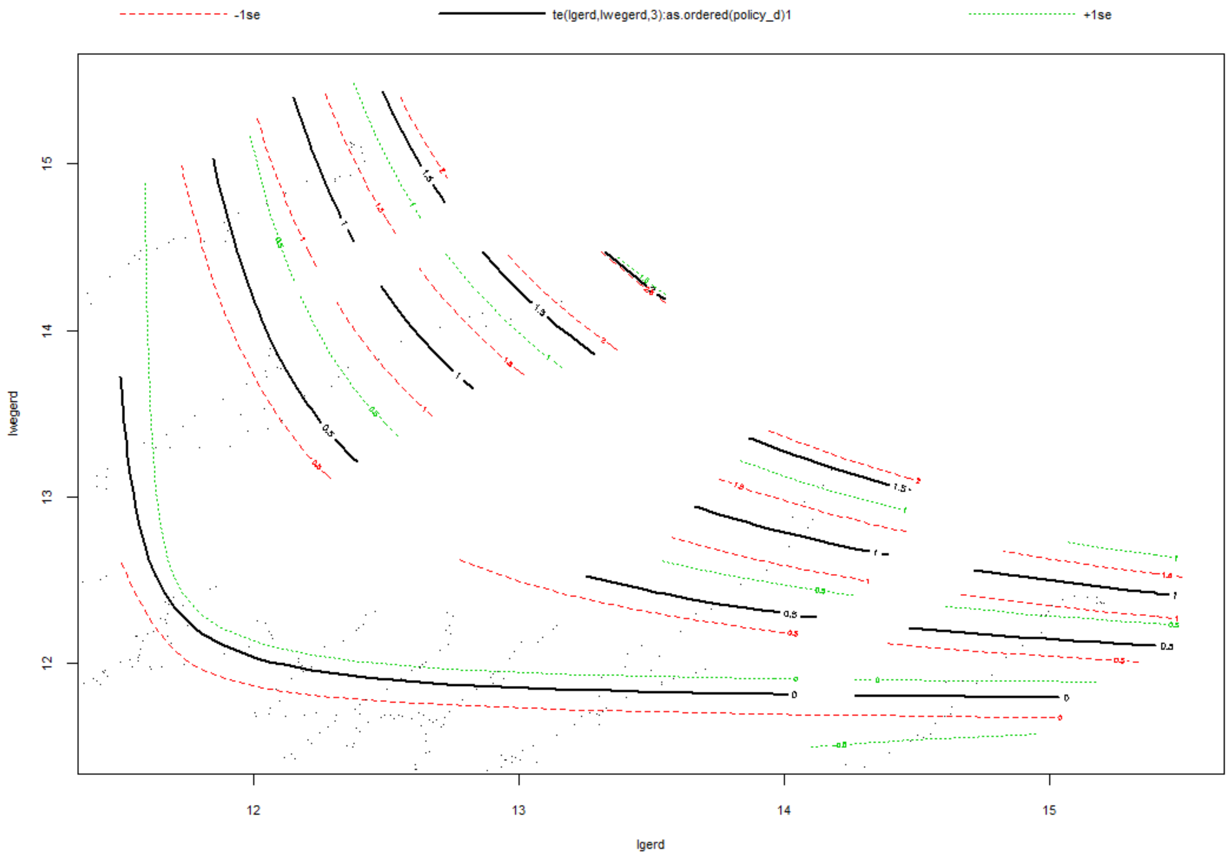


Table 1 – Model selection

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