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DOES ENVIRONMENTAL POLICY STRINGENCY FOSTER INNOVATION AND PRODUCTIVITY IN OECD COUNTRIES?

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Abstract

In this paper we use panel data models and quantile regressions to test the “weak” and “strong” versions of the Porter hypothesis, using data from 14 OECD countries over the period 1990-2011. A newly-released environmental policy stringency index (EPS) provided by the OECD is used as an indicator of the stringency of environmental regulations in order to tackle endogeneity issues of proxies used in earlier research. The findings indicate that more stringent environmental regulations positively influence R&D expenditure, the number of patent applications and total factor productivity (TFP). The results show that environmental stringency has a positive effect on R&D, mainly for the lower quantiles (0.10, 0.25) of the distribution of R&D, whereas for the number of patent applications and total factor productivity, the effect increases for the highest quantiles (0.75, 0.90) of the distribution of the targeted indicators.

Key words: Environmental regulations, Porter Hypothesis, OECD, Innovation, Quantile regression.
JEL Codes: Q43, Q48, Q53.

1. Introduction

It is currently widely acknowledged, not only by scientists but also by policy actors, that climate change is a man-made phenomenon. It primarily occurs as a consequence of increasing economic activity, and the associated increasing concentration of emissions. It is also acknowledged that pollution is a negative externality and that market mechanisms do not seem to offer a solution, so governments are therefore expected to set environmental regulations (ERs) as an instrument to control emissions of greenhouse gases (GHG). Several emission reduction policies have been proposed and applied by developed countries to control pollution. Some of them focus on levying taxes and penalties, on the internalisation of costs through market-based mechanisms, such as the emissions trading system (EU ETS), or on offering tax advantages for the production of less polluting goods, as in the case of the automotive industry. As a consequence of these policies, companies face an increase in costs related to pollution-reduction expenditure. There have been different interpretations about how companies react to changes in their cost structure. Some economic theories predict that production activities could be relocated to countries with lax environmental regulations (pollution havens), whereas others claim that the comparative advantage of a firm is not primarily determined by differences in cost stemming from differences in ERs between countries, but rather by other factors such as quality or unit labour cost differences.

According to the pollution haven hypothesis (PHH), ERs involve higher costs and, as a consequence, harm firms' income accounts and profitability. ERs reduce the competitiveness of the companies located in the countries that adopt more stringent regulations.

Porter (1991) and Porter and van der Linde (1995) introduced a completely different approach to the PHH when considering the effects of the ERs on company investment decisions. They claimed that more restrictive environmental policies, when properly designed by governments, could improve firm competitiveness and encourage their innovation efforts. Porter (1991) argued that ERs can be used to fix a market failure (externality), but they also stimulate efficiency and research expenditures and positively influence production costs through promoting technological change. Jaffe et al. (1995) named this effect the Porter hypothesis (PH).

Some critics of the PH emerged in the mid-1990s. For instance, Palmer (1995) criticized the PH claiming that it did not have any theoretical background or empirical evidence to support it. Whalley and Whitehead (1994) argued that there was no evidence of secondary mechanisms to compensate for a part of the direct costs of companies caused by the ERs. Finally, Heyes (1999) argued that the benefits of companies could be higher than the costs when ERs are implemented and enforced, but this implies that the net costs of the regulatory action should be zero or even negative.

In order to address the concerns of the aforementioned critics, Jaffe et al. (1995) and Jaffe and Palmer (1997) shaped the initial approach of Porter (1991) and the theoretical concepts related to the hypothesis by introducing three versions of the PH, which are identified as the strong, the narrow and the weak. We will explain each of them in turn.

The strong PH is the dynamic version of the hypothesis. This version implies that ERs have a positive medium-term effect on both the sector affected by the regulations and on the overall economy because the companies are restructured to improve efficiency and productivity, achieving in turn a reduction in costs. Ambec and Barla (2002) developed a theoretical model to substantiate the hypothesis and concluded that ERs may increase the expenditure in R&D and the expected benefits of the companies simultaneously. Moho (2002) pointed out that the confirmation of the PH depends on the type of policy adopted.

The narrow PH is based on the idea that companies do not necessarily intend to take advantage of all the possibilities of new processes or products under normal market conditions. Changes due to certain types of ERs encourage companies to find new products or processes that allow them to comply with the regulations and improve their results. The ERs stimulate innovation and the benefits derived are higher than the costs. Finally, the weak version of the PH states that ERs encourage companies to maximize results subject to the new conditions, so that new opportunities arise. The ERs stimulate certain types of innovations but the opportunity cost of these innovations is greater than the net profit achieved.

This paper examines the weak and strong versions of the PH using newly-released environmental policy stringency index (EPS) data for a sample of 14 OECD countries over the period 1990-2011. We use sectoral data and base the empirical strategy on the Jaffe and Palmer (1997) modelling framework, recently applied by Rubaskina et al. (2015) to EU (European Union) countries. Rubaskina et al. (2015) however had to exclude large economies of the EU, namely Germany, France and Italy due to lack of data on pollution abatement and control expenditures (PACE), and additionally, they were unable to consider a number of recent environmental policies that came into force after 2006. The main advantage of using the EPS index data is that we are able to include these large economies and our data goes up to 2011.

The main results of the paper indicate that higher EPS-index values have a positive correlation with R&D expenditures, the number of patent applications and total factor productivity (TFP). The quantile regression results confirm that environmental stringency has a positive effect on R&D, but only for the lower quantiles (0.10, 0.25) when using 1-year lag for the EPS variable, and for all quantiles when 5-year lags are used, with a decreasing effect for higher quantiles. As regards the number of number of patent applications and total factor productivity, the effect of the EPS (1 and 5-year lags) increases for the highest quantiles (0.75, 0.90) of the distribution of the targeted indicators, namely patent applications and TFP.

The rest of the paper is organized as follows. Section 2 presents a review of the related literature. Section 3 outlines the empirical model and describes the data and variables used. Section 4 summarizes and discusses the main findings, and section 5 concludes.

2. Literature review

In this section we review a number of papers that are closely related to our work and that test the different versions of the PH. We mainly focus on revising recent studies covering different countries that test any of the three versions of the PH.

Starting with studies that test for the weak and narrow versions of the PH, Jaffe and Palmer (1997) propose an econometric model and apply it to data from the manufacturing industry in the US over the period 1976-1991, using R&D expenditure and patents as dependent variables. They conclude that the abatement costs that companies have to pay to comply with the ERs, measured with PACE, have a positive effect on R&D (weak PH), but they find little evidence to indicate that innovation, measured by the number of successfully-applied patents, is related to the compliance costs (narrow PH).

Lanjouw and Mody (1996) examine the relationship between ERs and R&D and also find support for the weak PH. They conclude that expenses in Germany, Japan and the USA, in order to comply with the new regulations, stimulate an increase in environmental-technology patent requests with a one- or two-year delay. An econometric model is estimated using as dependent variable the number of patent applications as a proxy for companies' innovation activities and the PACE as a proxy for the stringency in ERs.

Using a similar approach to test for the weak version of the PH, Brunnermeier and Cohen (2003) study environmental innovations in the US manufacturing industry related to PACE and to the application of ERs between 1983 and 1992. They find that environmental innovations, measured by the number of patent applications, react positively to PACE, but that higher monitoring and the reinforcement of controls on existing regulations do not encourage innovation. In addition, they find that environmental innovation occurs in industries with very competitive international markets.

Popp (2005) suggests that not only innovation induced by the policies should be taken into account when we analyse the link between innovation and ERs, but also innovation created without political intervention and dissemination of new technologies in different regions or countries. In another paper, Popp (2006) examines the relationship between innovation, measured by patents, and the diffusion in the pollution-control equipment in electric power plants in Japan, Germany and USA, with regulations to reduce emissions of sulphur dioxide (SO_2) and nitrogen dioxide (NO_x). He concludes that innovations are clearly related to the increase of stringency inside the own country, but do not respond to legislative changes of other countries. De Vries and Withagen (2005) examine the relationship in the reduction of SO_2 emissions, proxied by the number of patents, and ERs, between 1970 and 2000 in 13 OECD countries. They conclude that environmental policies encourage innovation in new technologies, but the results are not robust to changes in the model specification.

Carrion-Flores and Innes (2010) study the emissions of 127 manufacturing industries between 1989 and 2004, and find that innovations contribute to the reduction of emissions. These innovations were influenced by environmental policies, but at a low ratio (environmental policy multiplier). Johnstone et al. (2010), using panel data for 25 countries over the period 1978-2003, examine the effect of environmental policies on technological innovation in the renewable energy sector, measured using the number of patent applications. They confirm the weak version of the PH, and conclude that certain types of policies, such as energy subsidies or emissions trading certificates, are necessary to encourage innovation in energy production sectors, such as that of solar energy, with higher costs. Lee et al. (2011) investigate the change in the number of patents on emissions control technology in the US automotive sector as a response to ER over the period 1970-1998.

They conclude that government intervention requiring the adoption of new technologies encourages businesses to innovate. Along the same lines as Popp (2005), the study shows that the increasing innovation in American companies caused by the temporary effect induced by ERs is higher than that of foreign companies within the same market.

Another dependent variable used to test of the validity of the weak PH is R&D expenditure. Kneller and Manderson (2012) use it to consider the relationship between regulations and innovation in the manufacturing industry in the United Kingdom from 2000 to 2006. The authors suggest that the pressure on companies to reduce their emissions, measured by its abatement costs, stimulates R&D in environmental capital, but this effect cannot be extended to all types of R&D. Furthermore, they point to potential crowding-out effects of environmental on non-environmental research, but this point is not definitively proved.

Lanoie et al. (2011) is one of the few empirical studies that tests the three versions of the PH using data from a survey of business managers for seven OECD countries. They find significant support for the weak version, explained by the research and development responses in the environmental sector to more stringent regulations. They also find support for the narrow version, when using environmental results as a response variable instead of R&D expenditure. However, no significant evidence is found for the strong version when using business results as a response variable. The main shortcoming of this study is that it is mainly descriptive in nature.

Using a similar approach to Jaffe and Palmer (1997), Rubashkina et al. (2015) also study the weak and strong version with data for manufactures in 17 European countries between 1997 and 2009. They find evidence of the weak version of the PH when linking PACE with patents and R&D, but do not find any evidence when using productivity (strong version of the PH).

Similar to Rubashkina et al. (2015), a number of empirical studies use total factor productivity (TFP) or, the so-called (OECD) multifactor productivity, as an indicator for business results to validate the strong version of the PH. For instance, Berman and Bui (2001) examine the effect of water quality regulations on productivity in oil refineries in Los Angeles (USA) between 1979 and 1992. They report a higher productivity from 1987 onwards compared with lower productivity in other plants. Most studies on productivity and ERs have focused on the manufacturing industry, as for example, Alpay et al. (2002). They show that environmental restrictions in the food manufacturing sector between 1971 and 1994 led to a reduction of the companies' results in some cases. In particular, they found no effect on productivity in the US linked to ER, whereas an improvement in productivity was found in Mexico.

Murty (2003) use data from 92 sugar industries in India between 1996 and 1999 and find some support for the PH, in the sense that ER on water conservation improves the technical efficiency of the companies. Along similar lines, Lanoie et al. (2008) investigate the strong version of the PH in the Canadian manufacturing sector in the province of Quebec and reach three main conclusions: although the effect of contemporaneous ER on productivity in levels is negative, it becomes positive when using lagged values of ER, as Porter already suggested; finally, the positive effect is magnified by greater international competitiveness.

Rutqvist (2009) studied the effect of ER in 48 highly-pollutant manufacturing companies in the US (aggregated into three groups) from 1999 to 2005 on the evolution of the employment to contrast the strong and narrow version of the PH. On the one hand, the results do not support the strong version of the PH in the sense that ER does not improve the competitiveness of the companies, but rather companies react by compensating the increase in costs through increased technological innovation in order to maintain international competitiveness. On the other hand, he points out that the results present heterogeneity with regard to the sub-sector studied and recommends the creation of flexible environmental policies such as, for example, market-based mechanisms. Greenstone et al. (2012) found that air quality regulations to reduce SO_2 emissions, atmospheric suspended particulates concentration and ozone level negatively affect productivity in the manufacturing plants of the USA, whereas carbon monoxide emissions regulation positively affects it.

Rexhäuser and Rammer (2014) use a very detailed firm-level dataset from the German part of the Community Innovation Survey. They distinguish between voluntary regulations and induced environmental innovations and find that environmental regulations affect regulation-driven innovation more than voluntary innovations and that in general, the strong version of the PH does not hold true. Nevertheless, the results should be interpreted cautiously because data from surveys from the German companies could be biased.

A number of recent studies on this subject use exports as a performance indicator, and are based on estimations of gravity models of trade, such as the work of Costantini and Mazzanti (2012). They test for the strong and the narrow version of PH with international trade data of EU15 and 145 importing countries from 1996 to 2007. These authors reject the hypothesis when using aggregated exports, but accept it in the case of exports in environmental goods. De Santis (2012) also obtains mixed results, estimating a gravity equation with data from 1988 to 2008 and finds a negative effect of ER on bilateral trade in EU-15 countries, but a positive effect when using the entry into force of the major environmental treaties (UNFCC, Kyoto and Montreal).

The findings of Sauvage (2014) concur, stating that regulations positively influence the specialization in environmental products of the companies located in the country. As a result, these companies improve their competitive advantage and increase their exports because of the rise in interest of other countries to adopt those regulations. This research uses the environmental policy stringency index (EPS) as a proxy for ER.

Finally, Groba (2014) uses a gravity equation to analyse the role of environmental policies on renewable energy and trade barriers on the export of electronic components of solar energy in 21 OECD countries and 118 exporting and importing countries between 1999 and 2007. The results confirm the narrow version of the PH and, in addition, indicate that the sooner a country introduces ER, the greater the increase in exports increases. A summary of the main results obtained in the empirical studies testing the different versions of the PH is presented in Table 1, indicating the target variables, the sample of countries and years and whether the PH is confirmed or rejected.

Table 1. Summary of empirical studies on the Porter hypothesis

Study	**Dependent variable**	**Data**	**Porter H**
Weak Porter			
Jaffe and Palmer (1997)	Patents and R&D	US Manufacturers	Weak support in patents/Support in R&D
Lanjouw and Modi (1996)	Patents	Germany, Japan and the US	Support

Brunnermeier and Cohen (2003)	Green Patents	US Manufacturers	PACE/No Regulations
Popp (2006)	Green Patents	Germany, Japan and the US	RMA own country
De Vries and Withagen (2005)	Green Patents	3 OECD countries	Support
Carrión-Flores and Innes (2010)	Green Patents	127 US Manufacturers	Support
Johnstone et al. (2010)	Green Patents	25 countries	Support
Lee et al. (2011)	Green Patents	US enterprises	Support
Lanoie et al. (2011)	Patents	7 OECD countries	Support
Kneller and Manderson (2012)	R&D	UK Manufacturers	Support R&D ER/Not in total (crowding-out)
Rubashkina et al. (2015)	Patents and R&D	17 EU countries	Support in patents/No support in R&D
Strong Porter			
Berman and Bui (2001)	Productivity	Los Angeles Refineries	Support
Alpay et al (2002)	Productivity	Mexico and the US Manufacturers	Yes Mexico/ No US
Murty (2003)	Productivity	92 Indian enterprises	Yes
Lanoie et al. (2008)	Productivity	Quebec	Yes, lagged and international sectors
Lanoie et al. (2011)	Productivity	7 OECD countries	
Rutquist (2009)	Productivity	48 US manufacturers	No, but sub-sectors variability
Greenstone (2010)	Productivity	USA Manufacturers	No, Ozone and particles/Yes CO
Rexhäuser and Ramer. (2010)	Productivity	German enterprises	No support
Rubashkina et al. (2015)	Productivity	17 EU countries	No support
Costantini and Mazzanti (2012)	Exports	EU-15 countries	No support
De Santis (2012)	Exports	EU-15 countries	No ER/Yes treatments (Kyoto, Montreal)
Sauvage (2014)	Exports	OECD countries	Support in Env. goods (narrow)
Groba (2014)	Exports	21 OECD countries	Support in Env. sector (narrow)

3. Empirical strategy

3.1. Model specification

We base our empirical application on the model first used by Jaffe and Palmer (1997) and extended by other authors. The model is specified as:

$$C = f(ER, Z) \quad (1)$$

where C is the competitiveness or innovation indicator, ER is the restriction level of regulations and Z are control variables for measuring the heterogeneity of each country-sector. Table A.1 summarizes the main studies that have estimated a similar model. The second column lists the indicator used to measure performance, the third contains the list of explanatory variables and finally, column 4 reports the estimation technique.

We first use Jaffe and Palmer (1997) model as a baseline model to test for the weak version of the PH. Next, in order to test for the strong version, we estimate the model using productivity as dependent variable. We also use the extended model based on Rubashkina et al. (2015), which includes additional explanatory variables. Finally, we apply an innovative econometric approach, not yet used in the existent literature, namely quantile regression. By applying quantile estimation, we are able to account for differences between the most innovative countries and the least innovative ones.

The first model, based on Jaffe and Palmer (1997), to test the relationship between the RE and innovation is given by:

$$\log(RD)_{ijt} = \beta_1 \cdot \log(VA)_{ijt} + \beta_2 \cdot \log(GRD)_{jt} + \beta_3 \cdot \log(EPS)_{i,t-1} + \alpha_{ij}^R + \mu_t^R + \epsilon_{ijt}^R \qquad (2)$$

where i denotes countries, j denotes sectors and t time. RD denotes research and development expenditure. VA is value added in sector j. GRD includes government R&D expenditure in sector j.

EPS is the environmental policy stringency index (EPS), built by the OECD, as an indicator for the level of ERs. Jaffe and Palmer (1997) used pollution abatement cost and expenditures (PACE, from Census Bureau's Pollution Abatement Cost and Expenditure Survey in the US) as a proxy of ER. α_{ij} and μ_t denote country-sector and year fixed effects, respectively. We use the EPS lagged one and five years to control for the effect of short- and long-term regulations on innovation projects. We will refer to the model as expressed in equation (2) as model 1a.

We formulate a second equation to estimate the effect of the ER on the number of patents,

$$\log(PT)_{it} = \gamma_1 \cdot \log(VA)_{it} + \gamma_2 \cdot \log(FPT)_{it} + \gamma_3 \cdot \log(EPS)_{i,t-1} + \alpha_i^P + \mu_t^P + \epsilon_{it}^P \qquad (3)$$

In addition to the explanatory variables included in the first model, model (3) also includes patent applications (PT) by companies in year t, as well as patents successfully applied for in the country for foreign companies (FPT). This model includes country and time fixed effects and one- and five-year lags of the EPS indicator. We refer to equation 3 as model 1b.

In the third specification, proposed productivity is used as the dependent variable to test for the strong hypothesis of Porter (model 1c):

$$\log(TPF)_{ijt} = \gamma_1 \cdot \log(VA)_{ijt} + \gamma_2 \cdot \log(GRD)_{it} + \gamma_3 \cdot \log(EPS)_{i,t-1} + \alpha_{ij}^{P} + \mu_t^{P} + \epsilon_{ijt}^{P} \quad (4)$$

where TFP denotes total productivity measured as multi-factor productivity in sector i and year t. EPS environmental policy stringency index in country i and time t

The model also includes country-sector and time fixed effects. We will refer to equation 4 as model 1c.

These models, originally used to test the PH using manufacturing industry data in the US have been extended to a more general version in which the independent variable of interest, TI, is the improvement in the global or environmental economy, which is a function of the level of national environmental regulations EPS, and other independent variables that reflect the differences between sectors or countries (Rubashkina et al., 2015). The extended specification is given by:

$$\log TI_{ijt} = \beta \cdot \log EPS_{ijt-q} + \gamma \cdot \log Z_{ijt-1} + \alpha_{ij} + \mu_t + \epsilon_{ijt} \quad (5)$$

where TI_{ijt} is the economic effect of regulations: research (R&D), innovation (patents) or productivity in country i, sector j and year t.

EPS_{ijt} is the environmental stringency indicator EPS.

Z_{ijt} is a vector that includes variables with country or sectoral variation or both to reflect the heterogeneity

The variables used to estimate sectoral differences are:

In all models: value added, import penetration rate, export intensity and the variation rate in the number of workers by sector and country as a proxy of the cyclical change. Other authors used enterprise birth and death rates in each sector, but these last two variables are not available for all countries in our sample.

In R&D estimation (model 2a): government expenditure in R&D and R&D investment stock.

In patent estimation (model 2b): government expenditure in R&D and patents stock.

In productivity estimation (model 2c): common variables.

The model in Rubashkina et al. (2015) applies different lags to PACE: one year for R&D model and two years for patent model. They use instrumental variables to avoid endogeneity issues of PACE within the model. The EPS indicator does not present any endogeneity issues because, as we will explain in the next section, it is a complex index made in such a way that it is exogenous to company behaviour. We will use lags 1 and 5 to compare our results with model 1.

Finally, we estimate the extended model using quantile regression techniques to observe the different behaviour between the most innovative countries (USA, Japan and Germany) and the rest.

The quantile estimation model was introduced by Koenker and Basset (1978) and uses linear programming methods to estimate the coefficients of the independent variables conditioned on the value of the dependent variable by quantiles. The general form is given by,:

$$y_i = \beta_q \cdot x_i + e_i \qquad (6)$$

where β_q refers to quantile, so we will have several coefficients per variable to be estimated as fixed percentiles, because the coefficient calculation is determined by the values within each quantile. We should bear in mind when interpreting the model that coefficients are significantly different from zero and significantly different from the coefficients estimated by ordinary least squares. This model avoids heterogeneity problems in the data distribution and is more robust than OLS in the presence of heteroscedasticity, outliers and structural change. It allows us to draw conclusions about the influence of the independent variables in relation to the distribution of the dependent variable.

As we have shown before, R&D expenditures and patent applications are not distributed symmetrically because three countries, USA, Japan and Germany, represent 75% of the total volume of those activities. This heterogeneity in the distribution of the dependent variables, estimated with fixed effects by country-sector, can cause distortions in the models for quantiles. Canay (2011) proposed a two-step method to take the rich analysis offered in fixed effects panel data and the information about the heterogeneous effects in the variation of the dependent variable in the quantile estimation.

The method, already applied in some empirical work, such as Martínez-Zarzoso et al (2014), consists of two steps. First, fixed effects estimation is applied and the country-sector fixed effects are saved. In the second step, the country-sector fixed effects are used to transform the dependent variables. Then, we apply the quantile regression of the transformed dependent variables model. The transformation can be expressed as:

$$X'_{ijt} = X_{ijt} - \alpha_{ij} \qquad (7)$$

3.2. Data and variables

We use an unbalanced-panel dataset for 14 OECD countries, namely, Australia, Belgium, Czech Republic, Finland, France, Germany, Hungary, Italy, Japan, Korea, Norway, Portugal, United Kingdom (UK) and the United States (US). For the model with TFP as the dependent variable, Korea, Norway and Portugal are excluded because of a lack of data.

The dependent variables are:

RD - business expenditure in research and development measured in USD at constant prices (PPP-2010) by country, sector, and year.

PT - the number of patent applications made simultaneously in the three main offices of the world (Triadic patent: European Patent Office, the United States Patent and Trademark Office and in the Japan Patent Office) by the inventor country.

TFP - the multi-factor productivity (total factor productivity, TFP) by sector, country and year.

The independent variables are:

EPS - the proxy for environmental regulations, the environmental policy stringency index built by the OECD.

VA - the gross value added (in millions of monetary units) by country, sector and year in current prices and in national currencies. These have been converted into PPP constant USD using a correction factor from the World Bank Development Indicators database.

M_PE - the import penetration level by country and year, measured as the ratio of imports over the sum of domestic production (GDP) and imports.

X_IN - the export intensity by country and year, measured as the ratio of exports over domestic production (GDP).

K_RD and K_PT are, respectively, the R&D stock and the patent stock by country, sector and year, constructed using the perpetual inventory method and taking 10 years as useful life.

GRD - government expenditure in R&D by country.

F_PT - the number of patent applications from non-resident companies in national offices, by country and year[1].

LAB - the variation rate of the number of workers by sector, country and year, measured as the natural logarithm of the number of workers of a given year minus the natural logarithm of the number of workers in the previous year.

Most data were extracted from the OECD Statistical Office, except data on imports, exports and GDP that were extracted from the World Development Indicators of the World Bank and the total Productivity factor from EU KLEMS database.

The sectors considered in this study are: farming, mining, manufacturing, electricity, construction and services. The model for patents is only disaggregated by country.

We offer a detailed explanation of the most important variables used for testing the PH in the next subsections.

3.2.1. Research and Development

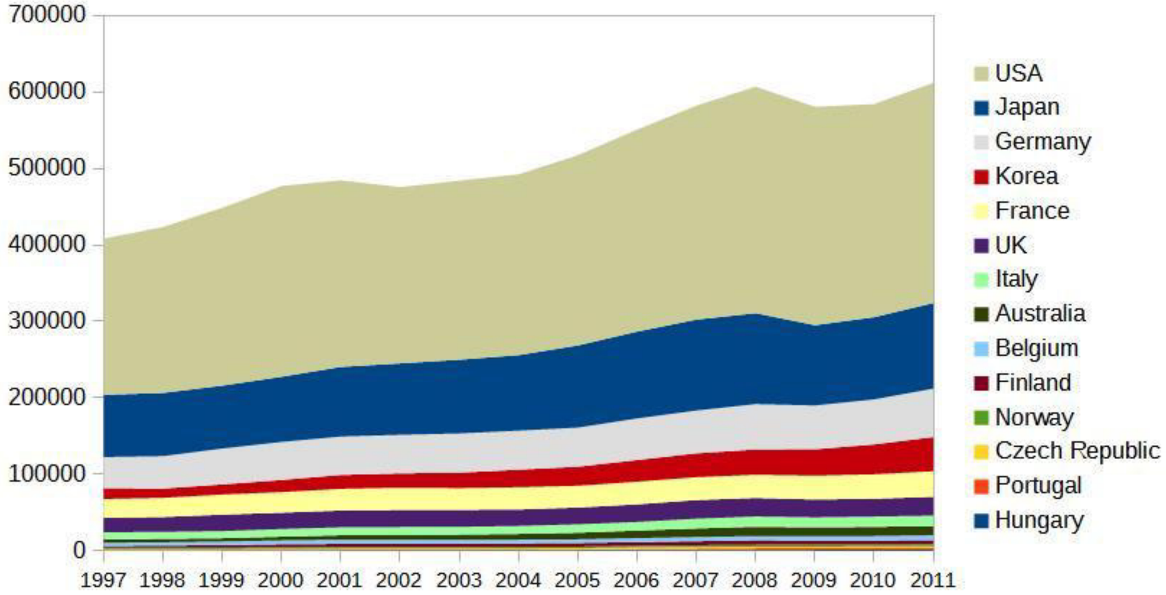
Research and development expenditure (R&D) is a good indicator of the innovation efforts of each country. It covers three activities, namely, basic research, applied research and experimental development; all necessary to increase the stock of knowledge and its use to develop new applications. Among the indicators released by the OECD in this subject, the aggregate gross domestic expenditure in R&D (GERD) is frequently used because it takes into account the resident company, government, university and research institute

[1]Data from EU KLEMS database, versions 3 (base year: 1995) and 4 (base year: 2005). The second version changed the base year from 2005 to 1995. The data for Australia was taken from the *Australian Bureau of Statistics*, changing the base year from 2012 to 1995.

expenditure. We use GERD data in purchasing power parity (PPP) constant dollars of 2010 to estimate model (1) in its different versions.

Figure 1 shows that the country with the highest R&D expenditure rate is the US (47% of total), followed by Japan (18%), Germany (10%), Korea (7.3%) and France (5.5%). Other countries of the sample invest less than 5% of total R&D expenditure. It should be noted that three countries, the US, Japan and Germany, together account for over 75% of all R&D expenditure.

Figure 1. R&D expenditure. Evolution over time by country



3.2.2. Patents

The PATSTAT database was created by the European Patent Office (EPO) at the request of the OECD and offers an enormous amount of information about more than 80 world patent offices, the major ones being: the EPO, the US Patents and Trademark Office (USPTO), the Japan Patent Office (JPO), and two Patent Cooperation Treaty offices: WIPO and NSF1[2]. According to Haščič (2014), the number of patents as an indicator of technological innovation presents several problems. Firstly, the patent system protects the legal right to exploit an

[2]WIPO is the *World Intellectual Property Organization* and NSF is the *National Science Foundation.*

innovation in the territory of the office where the request has been made. Patent applications should be requested in different patent offices of the world or use an international procedure in order to protect an invention worldwide. This fact leads to a number of problems. In particular, protection regulations are locally-focused and therefore heterogeneous; the same innovation can be registered multiple times, in as many geographic areas as one requires, increasing the potential of being counted twice; improvements to protection are implemented at different levels: locally, nationally, regionally and globally; companies can register defensive patents to prevent other companies from registering their product. Secondly, some innovations are not patented because they have another type of protection or the company preferred to keep it a secret. Thirdly, the value of patents is a heterogeneous and biased indicator for innovation because there are many patents applications that have low economic value and very few that have a high value. Finally, patent request tendencies are very different from one country or sector to the next.

In order to avoid some of the abovementioned problems, the concept of patent families has been developed. A family is a set of applications or patent approvals that are listed in different offices and are interconnected because they share one or more common fields. Martínez (2010) outlines the advantages of using patent families. Namely, it avoids double counting the same innovation; it does not include local requests, usually with lower economic value; it includes patents with international impact, with greater economic value and with higher utility as a best indicator of economic trends in innovation; it eliminates the time bias caused by the fact that to extend the applications worldwide, a company usually has to wait one year from the first request made to the local office.

The PATSTAT database, built by the OECD, provides data on triadic families. This patent family count patents with common characteristics from the three most important offices in the world: the EPO, USPTO and JPO[3]. The triadic patent family represents almost 21% of total patent requests. The advantages of the triadic patent family are that it is a good indicator of

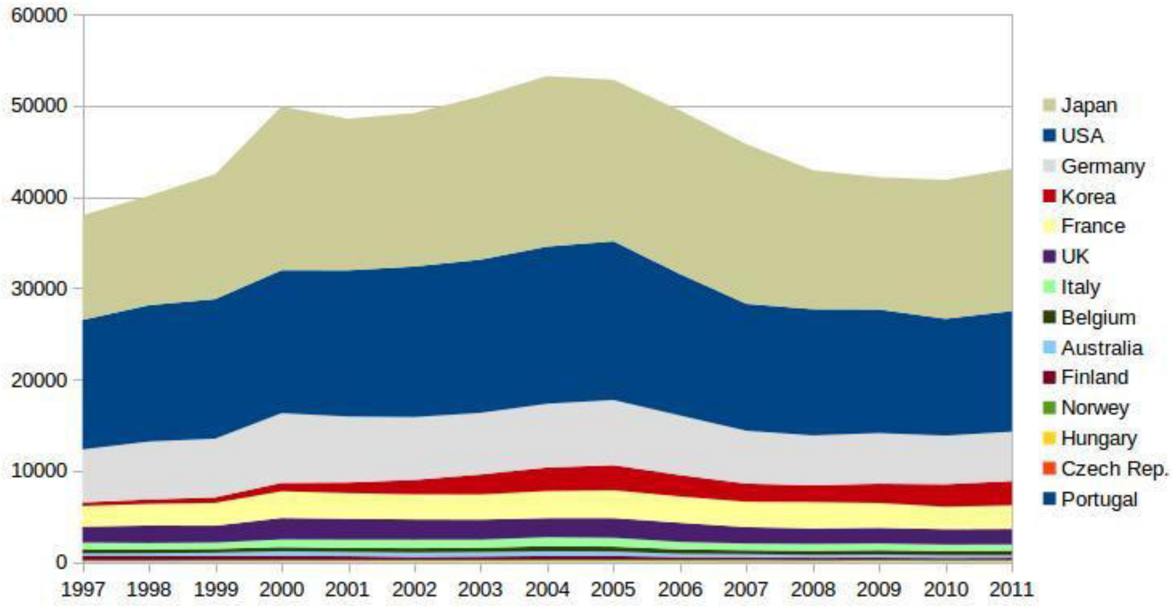
[3]They count the requests by the European and Japanese patent offices plus the patents granted by the American Office (adjusted in 18 months as the time required by the USPTO to publish the application or, for older patents, 36 months as the average time required to study and report on each application). For this reason, data publication is delayed 2 years.

patents with economic value because the companies are obliged to make an economic and management effort to achieve them; it is a good indicator of the innovation of the companies and it safely removes any double accounting issues (Martínez, 2010). The main disadvantage is its restrictive conditions that do not allow a detailed analysis by technologies because the frequency of zeros in the data set is very high (Haščič 2014).

In this paper we use data of the triadic patent family by countries to estimate the relationship between ER and innovation. This family is, therefore, a good indicator of the company's results of different countries in relation to the R&D effort and, is a good proxy of innovation in new products and processes because it has a high economic value.

It would be reasonable to expect the number of patents registered in registry offices to correlate to the effort made in R&D. This is generally the case, but as Figure 2 indicates, some differences do occur. The US, with an effort of 47% out of the total R&D expenditure, reaches just 19.1% of total patents; elsewhere, Japan with an effort of 18%, accounts for 36.2%; and Germany with an effort of 10%, accounts for 7.8%. The differences can be explained by the national laws on intellectual property rights and the accountancy criteria used. A possible bias in this variable should be borne in mind.

Figure 2. Number of patent applications over time by country



3.2.3. Total Factor Productivity

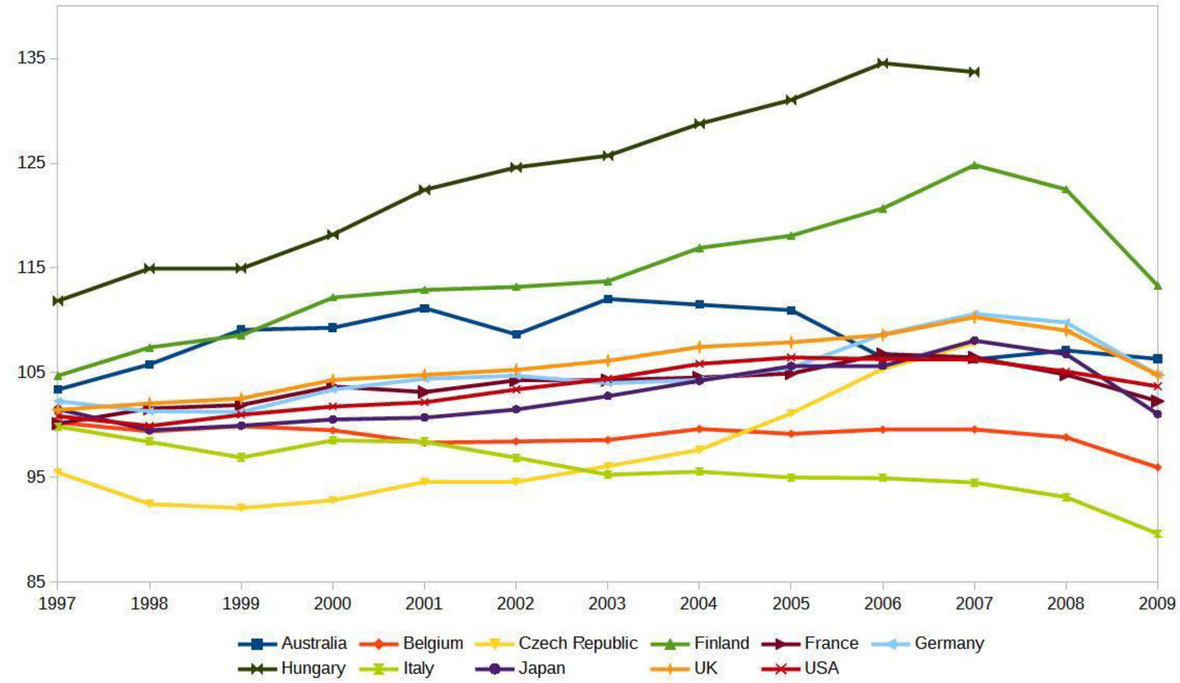
Total Factor Productivity (TPF)[4] represents how efficiently capital and labour factors are used in the production process. Changes in the TPF register alterations in a company's managerial practices, use of trademarks, organization structures, general knowledge, the effect of networks, production externalities, economies of scale and cost adjustments (van Beveren, 2012). TPF, due to its general nature, is a good indicator to test the strong version of the Porter hypothesis because it summarizes the effects that the ER have on competitiveness and the results of the firms.

TFP is from the EU KLEMS database. Figure 3 illustrates the evolution of productivity over time and across countries. Most countries show increasing TFP over the years from 2000 to 2007, except Belgium and Italy (5% decline in the latter). Hungary and Finland's TFP increased by 19% while that of the Czech Republic increased by 13%. In the subsequent period, 2007-2009, there is a general reduction of TFP levels.

According to van Beveren (2012), this indicator presents certain shortcomings when used in a model. In particular, TFP follows the economic cycle, there are factors that are not accounted for and are difficult to quantify, such as the product quality and design, and it is also sensitive to other effects such as imperfect markets.

Figure 3. TFP evolution over time by country

[4] Introduced by Solow (1957).


135
125
115
105
95
85
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Australia
Belgium
Czech Republic
Finland
France
Germany
Hungary
Italy
Japan
UK
USA

3.2.4. Environmental Policy Stringency Index

An indicator to measure ER at a country level is needed to test the PH. Ideally it should combine quantitative and qualitative information related to environmental policy (laws and regulations) and should be comparable across countries (Botta and Koźlak, 2014).

The pollution abatement cost and expenditures (PACE) has been used as a proxy of ER stringency in many empirical studies, especially those for the US. However, as an indicator, it has a number of shortcomings. First, PACE variations are caused by different factors and not only by the adaptation of the company to the ER. Second, companies can reduce the ER effects through decisions that do not require expenditure, for example, outsourcing or offshore agreements. Third, economies with an important heavy industry most likely present a higher level of expenditure than service economies (Brunel and Levison, 2013). Finally, PACE presents comparability problems over time and across countries, and endogeneity concerns connected with other economic indicators are also an issue (Koźluk and Zipper, 2014).

We use the environmental stringency index (EPS) to avoid these problems. The composite indicator is built with individual indicators on environmental policy instruments (15 market-based and 3 nonmarket-based)[5]. Figure 4 shows a diagram with the detailed instruments used to build EPS by policy and indicator.

Figure 4. EPS index and its components

[5]EPS does not include indicators for nuclear and hydroelectric power generation or land-use. Both use voluntary regulations indicators, which may cause a certain bias in countries, such as Japan, whose ER is based on this kind of measure.

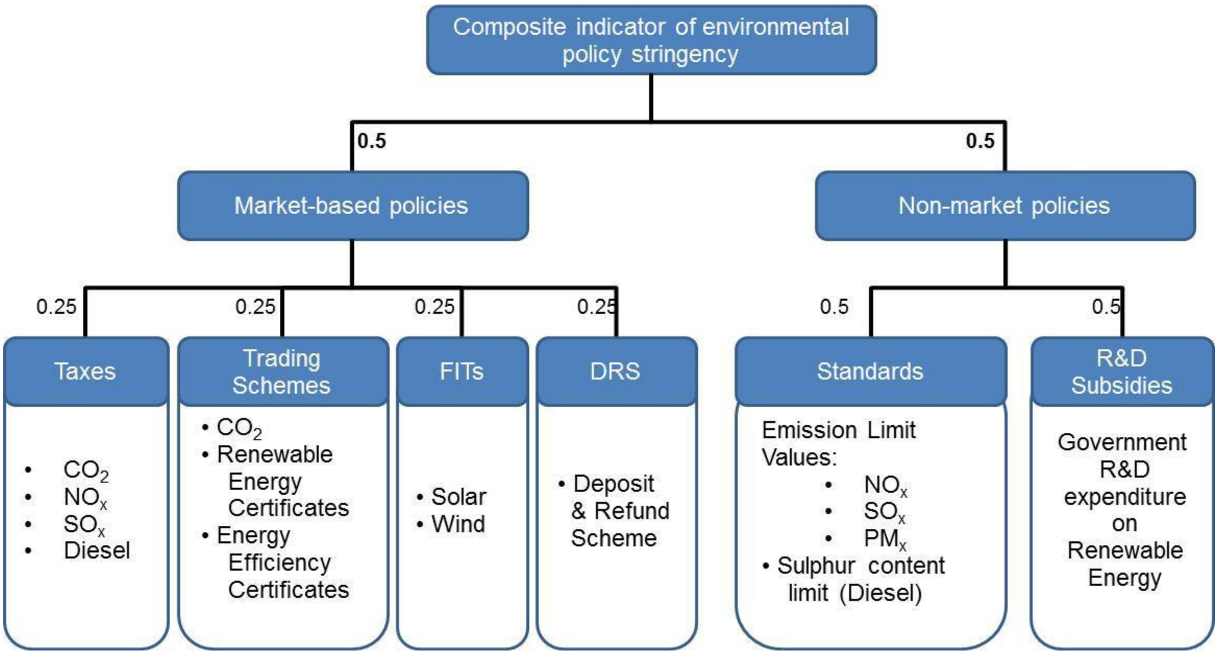


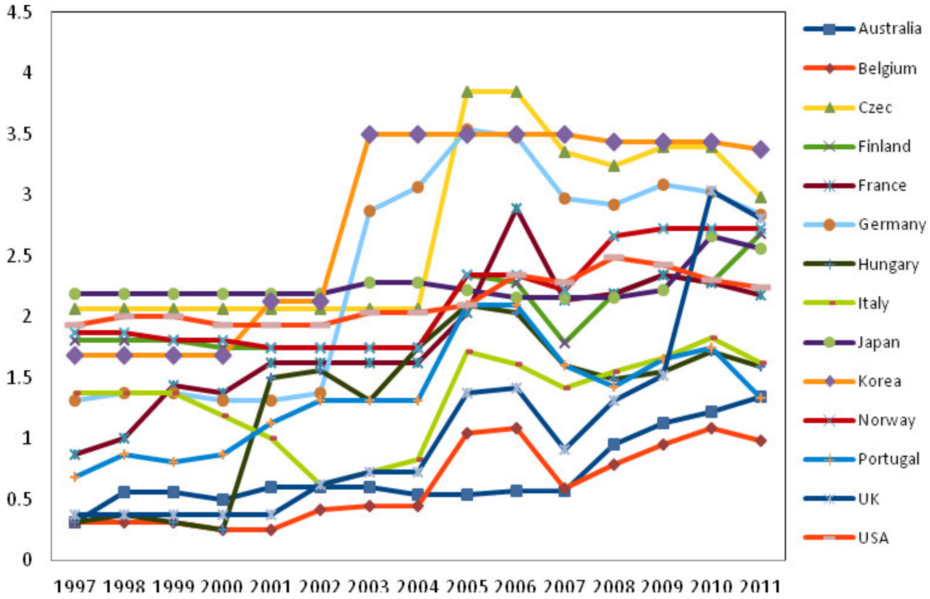
Table 2 in the Appendix and Figure 5 illustrate the index evolution by country. All the countries increased their index values from 2002 onwards. The highest values for the period 2002-2011 are for the Czech Republic, Korea and Germany (around 3 points). We do however observe a slight reduction in all countries in the last two years.

EPS variations by country, presented in Table 2, show wide differences across countries. Whereas the EPS in Great Britain is 6.5 times the initial level at the end of the period, in Hungary and Australia, the EPS quadrupled and tripled, respectively; and in the US, Japan and Italy, it only rose by about 15%.

Table 2: Variation of the EPS index (1997 - 2011)

Australia	Belgium	Czech Republic	Finland	France	Germany	Hungary	Italy	Japan	Korea	Norway	Portugal	UK	USA
332 %	216 %	45%	48%	149 %	116 %	408 %	18%	17%	100 %	45%	95%	650 %	15%

Figure 5. EPS index, evolution over time by country



4. Main results

The main results for the baseline model when R&D is used as dependent variable are presented in Table 3 (model 1a). The coefficient of EPS (five-year lagged) is positive and statistically significant at the 10% level, whereas it is not significant when the first lag is used. This means that environmental policies do not affect the R&D expenditure decisions of the companies in the following year, but do however encourage an increase in expenditure after a period of five years. This supports the weak version of the PH.

The variable that represents the economic size of the country and the sector (VA) is significant and positive, showing that more R&D is dedicated to sectors with a greater weight in the economy. The coefficient for government R&D expenditure is significant and negative, which can be interpreted as a crowding-out effect of business investment.

Table 3. Results baseline model

Depend. Var:	R&D (1a)		Patents (1b)		TFP (1c)	
	k=1 lag	k=5 lags	k=1 lag	k=5 lags	k=1 lag	k=5 lags
Ln EPS(t-k)	0.01 (0.063)	0.14 (0.08)*	0.16 (0.023)***	0.06 (0.02)***	0.06 (0.02)**	0.02 (0.01)
Ln VA	0.55 (0.10)***	0.23 (0.10)**	0.001 (0.003)	0.00 (0.00)	0.01 (0.03)	0.01 (0.03)
Ln GRD	-0.072 (0.021)***	-0.062 (0.029)**	-	-	0.01 (0.00)	0.001 (0.007)
Ln FPT	-	-	0.76 (0.04)***	0.61 (0.05)***	-	-
R^2	0.97	0.98	0.99	0.99	0.80	0.90
S.E.	0.55	0.45	0.15	0.13	0.08	0.07
F-stat	308.35***	340.74***	8212***	9266***	33.32***	46.64***

Note: *, **, *** denotes significance level at the 10%, 5% and 1% level, respectively. LS Model estimation with country-sector and time fixed effects. Heteroskedastic and Autocorrelation Consistent Standard errors reported in brackets. Newey-West correction used[6].

The environmental policy stringency index, EPS, is significant and positive for both one-year and five-year lagged values in model 1b. This result also confirms the weak version of the PH in the sense that regulations cause a reaction in the companies to offset the loss of competitiveness caused by an increase in costs to reduce pollution. The fact that the coefficient of foreign participation in innovation (FPT) is significant and positive highlights the multinational character of innovation.

Finally, the results of model 1c that estimates the strong version of the PH show lag sensitivity. The one-year lagged EPS is significant; whereas the five-year lagged EPS is not. This result implies a positive influence of the ER on the results of companies, but only in the short term. These results are in accordance with Rubashkina et al. (2015). However, the findings differ from those in Jaffe and Palmer (1997) concerning the EPS indicator, when R&D and patents are used as dependent variables. The authors found no-significant effects of environmental regulations on R&D and Patents.

We also use a one- and five-year lag on the EPS in the extended model to obtain the long-term effect on firms' innovation operations. The one-year lag is also used for other explanatory variables. The main results, shown in Table 4 indicate that in model 2a, the EPS variable is not statistically significant, which means that we cannot accept the Porter hypothesis for R&D expenditures in the extended model.

[6]In model 1b only country effects.

Table 4. Main results extended model

Dependent Variable:	**R&D (2a)**		**Patents (2b)**		**TFP (2c)**	
	k=1 lag	k=5 lags	K=1 lag	k=5 lags	k=1 lag	k=5 lags
Log EPS	0.03 (0.08)	0.12 (0.07)	0.097 (0.020)***	0.04 (0.02)**	0.05 (0.02)**	0.02 (0.02)
Log VA(t-1)	0.63 (0.127)***	0.29 (0.12)**	-0.001 (0.003)	0.00 (0.00)	0.06 (0.03)*	0.06 (0.04)
Log GRD(t-1)	-0.066 (0.02)***	-0.053 (0.03)*	0.01 (0.004)	0.013 (0.01)**	0.002 (0.01)	-0.003 (0.01)
Log KRD (t-1)	0.44 (0.067)***	0.27 (0.074)***	-	-	-	-
Log KPT (t-1)	-	-	0.68 (0.03)***	0.29 (0.05)***	-	-
X_IN(t-1)	-0.90 (0.29)***	-0.66 (0.35)*	-0.16 (0.11)	-0.18 (0.15)	-0.25 (0.07)***	-0.13 (0.08)*
M_PE(t-1)	0.06 (0.19)	-0.43 (0.22)**	0.57 (0.22)***	0.52 (0.24)**	0.03 (0.03)	0.02 (0.05)
LAB(t-1)	0.49 (0.26)**	0.30 (0.31)	0.070 (0.077)	-0.006 (0.07)	-0.06 (0.06)	-0.03 (0.07)
R^2	0.97	0.98	0.99	0.99	0.82	0.90
S.E.	0.51	0.44	0.18	0.15	0.079	0.07
Fstatistic	349.44***	347.18***	5265***	5735***	35.55***	48.72**

* significant 10%,** significant 5%,*** significant 1%. LS Model estimation, fixed effects by country-sector and time, HAC correction (Newey-West)[7].

VA still determines R&D expenditure; the coefficient shows a positive relationship. The greater the capacity of countries and sectors to generate more value added, the greater their capacity to invest in research and innovation. Business expenditure (GRD) is negatively correlated with Public expenditure on R&D, which could indicate a crowding-out effect of private sector investment. The research and development stock (KRD) represents the investment knowledge accumulated by the companies. The coefficient of this variable has a positive sign and suggests that the accumulation of the past experience in expenditure on R&D stimulates innovative companies to continue to innovate. Export intensity (X_IN) is a proxy of the international competitiveness and surprisingly presents a negative sign. A negative sign could be indicating that more competition abroad (lower export intensity) could encourage innovation with markets stimulating companies to increase R&D expenditure in order to obtain a commercial competitive advantage. Five-year lagged import penetration (M_PE) has also a negative sign, which confirms Schumpeter's point of view, namely that the greater the foreign competition, the lower the innovation levels.

EPS is significant and presents a positive sign in model 2b both, with the one- and with the five-year lag meaning that ER influences the productivity of the research and development in the short term and in the long term. The magnitude of this influence is 10% and 4.3% increase in patents per EPS point increase, respectively.

[7]In model 1b only country effects.

The stock of patents (KPT) is also statistically significant and has a positive influence on the number of patent applications. The higher the protection levels of innovation, the greater propensity to continue patenting is. It is important to highlight that three countries of the sample represent 80 percent of the total patent applications. Import penetration (M_PE) also presents a positive sign, indicating that greater external competition in the internal market stimulates new patents.

The results obtained in models 2a and 2b related to the effect of the ER and the capital stock are similar to earlier studies (Rubashkina et al., 2015; Johnstone et al., 2010; de Vries and Withagen, 2005), but differ with respect to the influence of import penetration and exporting intensity. The set of selected countries in those papers, more homogeneous in the case of the EU countries with the exclusion of Germany, could explain this difference in outcomes.

Finally, in model 2c, similar to model 1c, EPS is significant and positive in the short term but, not significant in the long term. These results imply a weak confirmation of the strong PH, which conflicts with the results of Rubashkina et al. (2015), who found a non-significant relationship, and of Lanoie et al. (2008), who reported opposite results. The reduced size of the sample in those papers due to lack of data availability could be the cause of this discrepancy. To verify the results and to account for differences in countries with different levels of R&D expenditure or patent registration, we estimate a quantile regression model.

We estimate model 2 with one- and five-year lags and fixed effects, for quantiles 10, 25, 75, and 90. In addition to the R&D and patents models, with a wide variation of the respective dependent variable, we estimate the model with productivity for comparative purposes. Tables 5, 6 and 7 show the results for the panel-quantile estimations.

Table 5: Quantile estimation R&D

Dependent Variable:	R&D 1 lag				
	All Q	**Q=10**	**Q=25**	**Q=75**	**Q=90**
Log EPS(-1)	0.006 (0.04)	0.11 (0.04)***	0.053 (0.02)**	-0.03 (0.02)	-0.02 (0.02)
Log VA(-1)	0.63 (0.02)***	0.65 (0.01)***	0.64 (0.01)***	0.62 (0.01)***	0.60 (0.01)***
Log GRD(-1)	-0.06 (0.01)***	-0.13 (0.02)	-0.09 (0.01)	-0.06 (0.01)***	-0.04 (0.01)***
Log KRD (-1)	0.45 (0.01)***	0.52 (0.01)***	0.47 (0.01)***	0.40 (0.01)***	0.37 (0.01)***
X_IN(-1)	-0.96 (0.10)***	-0.83 (0.08)***	-0.90 (0.05)**	-0.81 (0.04)***	-0.73 (0.05)***
M_PE(-1)	-0.07 (0.01)***	0.05 (0.01)*** #	0.07 (0.01)***	0.05 (0.01)***	0.05 (0.01)*** #
LAB(-1)	0.21 (0.33)**	0.44 (0.18)** #	0.12 (0.12)	0.29 (0.26)	0.43 (0.31) #
DependentVariable:	R&D 5 lags				

	All Q	Q=10	Q=25	Q=75	Q=90
Log EPS(-5)	0.12 (0.03)***	0.17 (0.03)***	0.15 (0.02)***	0.06 (0.02)***	0.07 (0.03)**
Log VA(-1)	0.29 (0.01)***	0.32 (0.01)***	0.30 (0.01)***	0.30 (0.01)***	0.27 (0.01)***
Log GRD(-1)	-0.05 (0.01)***	-0.10 (0.02)***	-0.07 (0.01)*** #	-0.03 (0.01)*** #	0.004 (0.1)
Log KRD (-1)	0.27 (0.01)***	0.33 (0.01)***	0.30 (0.01)***	0.23 (0.01)***	0.19 (0.01)***
X_IN(-1)	-0.66 (0.05)***	-0.69 (0.06)***	-0.67 (0.05)*** #	-0.66 (0.03)*** #	-0.67 (0.05)***
M_PE(-1)	-0.43 (0.01)***	-0.43 (0.01)***	-0.43 (0.01)***	-0.42 (0.01)***	-0.42 (0.01)***
LAB(-1)	0.30 (0.25)	0.37 (0.22)	0.23 (0.17)	-0.08 (0.42)	-0.04 (0.48)

Notes: *, **, *** denote significance level at the 10%, 5% and 1%, respectively. All models are estimated with panel-quantile regression, which include time fixed effects. # indicates that the difference in coefficients is statistically significant at the 5% level.

Table 6: Quantile estimation for patents

Dependent Variable:	PT (1 lag)				
	All Q	Q=10	Q=25	Q=75	Q=90
Log EPS	0.09 (0.01)***	0.01 (0.01) #	0.016 (0.01) #	0.09 (0.01)*** #	0.11 (0.01)*** #
Log VA(-1)	-0.00 (0.003)	-0.00 (0.001)	0.00 (0.002)	0.00 (0.002)	0.00 (0.002)
Log GRD(-1)	0.01 (0.004)	0.02 (0.003)***	0.01 (0.002)***	-0.003 (0.002)	0.007 (0.006)
Log KPT (-1)	0.68 (0.007)***	0.72 (0.01)***	0.71 (0.004)***	0.66 (0.004)***	0.64 (0.006)***
X_IN(-1)	-0.16 (0.06)**	-0.33 (0.05)*** #	-0.25 (0.05)*** #	0.05 (0.034) #	-0.31 (0.10)*** #
M_PE(-1)	0.57 (0.10)***	0.81 (0.07) *** #	0.70 (0.08)*** #	0.32 (0.05)*** #	0.88 (0.16)*** #
LAB(-1)	0.07 (0.07)	0.02(0.06)	0.00 (0.03)	0.00 (0.06)	0.00 (0.06)
Dependent Variable:	PT (5 lags)				
	All Q	Q=10	Q=25	Q=75	Q=90
Log EPS(-5)	0.04 (0.01)***	0.02 (0.01) #	0.03 (0.01)** #	0.03 (0.01)*** #	0.02 (0.02) #
Log VA(-1)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Log GRD(-1)	0.01 (0.004)***	0.01 (0.004)**	0.008 (0.003)**	0.01 (0.005)**	0.03 (0.01)**
Log KPT (-1)	0.29 (0.01)***	0.34 (0.003)***	0.33 (0.003)***	0.28 (0.01)***	0.25 (0.02)***
X_IN(-1)	-0.18 (0.06)***	-0.13 (0.07)* #	-0.14 (0.05)** #	-0.18 (0.08)** #	-0.57 (0.27)** #
M_PE(-1)	0.52 (0.09)***	0.39 (0.10)*** #	0.41 (0.08)*** #	0.53 (0.14)*** #	1.11 (0.41)*** #
LAB(-1)	-0.006 (0.07)	0.00 (0.04)	0.00 (0.03)	0.03 (0.06)	0.00 (0.06)

Notes: *, **, *** denote significance level at the 10%, 5% and 1%, respectively. All models are estimated with panel-quantile regression, which include time fixed effects. # indicates that the difference in coefficients is statistically significant at the 5% level.

Table 7: Quantile estimation TFP model

Dependent Variable:	TFP (1 lag)				
	All Q	Q=10	Q=25	Q=75	Q=90
Log EPS(-1)	0.05 (0.007)***	0.04 (0.01)***	0.03 (0.004)***	0.06 (0.005)***	0.07 (0.007)***
Log VA(-1)	0.06 (0.002)***	0.07 (0.003)***	0.06 (0.001)***	0.06 (0.001)***	0.05 (0.003)***
Log GRD(-1)	0.00 (0.003)	0.002 (0.003)	0.002 (0.001)	0.005 (0.002)**	0.008 (0.003)**
X_IN(-1)	-0.25 (0.01)***	-0.24 (0.02)***	-0.24 (0.008)***	-0.26 (0.01)***	-0.27 (0.01)***
M_PE(-1)	-0.03 (0.002)***	-0.02 (0.002)***	-0.02 (0.001)***	-0.03 (0.001)***	-0.03 (0.002)***
LAB(-1)	-0.05 (0.06)	-0.09 (0.17)	-0.05 (0.07)	-0.06 (0.06)	-0.10 (0.15)
Dependent Variable:	TFP (5 lags)				
	All Q	Q=0.10	Q=0.25	Q=0.75	Q=0.90
Log EPS(-5)	0.02 (0.005)***	0.02 (0.006)**	0.02 (0.003)***	0.03 (0.04)***	0.04 (0.007)***
Log VA(-1)	0.06 (0.001)***	0.07 (0.002)***	0.06 (0.001)***	0.06 (0.002)***	0.05 (0.002)***
Log GRD(-1)	-0.003 (0.002)	-0.01 (0.004)**	-0.002 (0.002)***	-0.003 (0.001)*	-0.001 (0.003)
X_IN(-1)	-0.13 (0.01)***	-0.12 (0.02)***	-0.13 (0.01)***	-0.13 (0.01)***	-0.13 (0.01)***
M_PE(-1)	-0.02 (0.002)***	-0.02 (0.002)***	-0.02 (0.001)***	-0.02 (0.01)***	-0.02 (0.001)***
LAB(-1)	-0.03 (0.06)	0.00 (0.10)	-0.05 (0.04)	-0.04 (0.07)	-0.004 (0.04)

Notes: *, **, *** denote significance level at the 10%, 5% and 1%, respectively. All models are estimated with panel-quantile regression, which include time fixed effects. # indicates that the difference in coefficients is statistically significant at the 5% level.

We can highlight in the RD model (Table 5) that the EPS lagged 1 time shows a positive and significant coefficient for the 0.1 and 0.25 quantiles, implying that countries with relatively lower R&D increase expenditure when environmental policy stringency is higher. On the other hand, R&D expenditure in countries that invest relatively more is not influenced by increases in environmental policy stringency. When using EPS lagged 5 times (second part of Table 5), the EPS coefficient is positive and significant in all quantiles, meaning that environmental regulations encourage R&D expenditure, the effect being higher for countries that invest less in R&D.

It should be noted, with respect to the other explanatory variables, that in the short term GRD has a negative effect on private expenditures in the higher investment countries, while it is not significant in the lower investment countries. In the long term, however, the GRD coefficient is negative and significant in all the quantiles analysed. The results therefore indicate the existence of a crowding-out effect, particularly for the lower investors in the long turn (using 5 lags, second part of Table 5).

The coefficient of exports intensity is significant and has a negative sign in all quantiles. It denotes a negative influence of exports on R&D investment. In addition, the influence of an increase in international market competition is lower with a five-year lag. The coefficient of import penetration is significant. The coefficient of this variable is positive in the model with one-period lag, which could indicate that companies invest more in R&D over the short term to improve the competitiveness position through innovation in order to face the foreign competition in internal markets. However, with a five-period lag the coefficient is negative, which indicates that increasing competition in the local market is likely to reduce costs and improve their competitiveness.

Results for the Patent model are shown in Table 6. The coefficient of the one-year lagged EPS (in the first part of Table 6) is significantly different from zero and different from the estimation in the patent model for the higher patenting countries, and is not significant in the lower quantiles of the distribution. It means that a higher patenting activity is stimulated when the regulatory pressure increases between the innovator countries. This positive effect is weaker in the long run, when using the five-year lagged EPS. One-year lagged GRD shows a positive and significant influence in the number of patent applications in the less innovative countries, however it is not significant in the most innovative countries. The patent stock coefficient is significant and positive for all quantiles, without significant differences between them. Exports intensity shows a negative and significant coefficient, especially for the higher quantiles. These results indicate that a greater international market competition hurts the innovative activity of companies. Import penetration, with 0.88 and 1.11 coefficients in the 90 percentile, presents a positive influence on the number of patents in the countries of greatest patenting activity, in the same line as in the OLS model.

Finally in the TFP model, the EPS coefficients are significant and positive in every quantile (with magnitudes between 0.02 and 0.07) and for one and five period lags. This result confirms the strong version of the PH, as partially proven in model 2b (model with 1 lag).

5. Conclusions

When political authorities design environmental policies that society as a whole must comply with, the economic agents face a dilemma. On the one hand, they have to prioritize the conservation of the environment where we live and where future generations are also supposed to live. For this reason, governments and firms have to incur greater costs to apply the necessary measures to comply with environmental regulations. Furthermore, companies and governments face increasing foreign competition due to the globalization of the world economy and have to offer low prices in order to maintain competitiveness.

The consequences of a restrictive policy measure, from a classical perspective, on the operation of companies are always negative: companies have to buy or create resources to reduce pollution, which results in higher costs and lower benefits. If the policy-makers took this into account, it could influence their decisions.

Assuming the classical idea is true, authorities should only take policy-stringency measures when social and environmental benefits are higher than the cost which companies have to incur. Porter (1991) proposed a solution to the dilemma by questioning the classical idea and postulating that environmental regulations can encourage innovation and, as a consequence, could improve company results, for example, increasing productivity, so that cost will be partially or completely compensated. Since the early 1990s, when Porter (1991) stated the idea and Jaffe et al (2005) formalized it, the Porter hypothesis has been widely tested. The lack of accurate data to measure environmental regulations has been one of the main difficulties faced by most empirical studies to date.

The present study adds new evidence, in line with Jaffe et al. (1995) and Rubashkina (2015), using a new ER index, the EPS, for 14 OECD countries, which solves some of the problems related to the ER proxies used in existing literature.

The main results provide weak evidence of the PH, indicating that environmental regulations can have a positive influence on the decisions that companies adopt in relation to the results in innovation, measured by the number of patent applications. However, less innovative countries seem to be less affected by the environmental regulations, while the countries that already have an innovative tradition embodied in the rights of exploitation of the inventions, are influenced the most.

We also find a significant correlation between the ER and R&D expenditures of the companies for only the lower quantiles of the distribution of R&D in the short-run, but for all quantiles in the long run.

The main results indicate that ER also influences total factor productivity and provides support for the strong version of the Porter hypothesis.

Of particular note is the remarkable difference in terms of the effort in innovation among three countries, namely the US, Japan and Germany, when compared to the other countries. This is also reflected in the relationship we find between environmental regulations and patenting activities. The results indicate that when facing more stringent ER, unlike other countries, the US, Japan and Germany react by increasing their patent activities and, as a result, achieve long-term improvements in productivity.

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Appendix

Table A.1. Main studies using model (1)

Authors	Dependent Variable	Explanatory Variables	Estimation technique
Jaffe and Palmer (1997)	Patents and R&D	PACE, Added value, spending on Government foreign patent expenditure, R&D	LS with FE
Brunnermeier (2003)	Patents	PACE, the number of inspection visits, exports, value of industrial transport, industrial concentration and intensity of capital of companies	LS with FE, Poisson, Maximum likelihood (FE and RE) negative binomial
De Vries (2003)	Patents	PIB, value added, sulphur oxides emissions, and R&D	LS with VI
Lanoie (2008)	Productivity	Value of research on pollution control equipment ratio, OSH (regulation on safety in the workplace index), changes in production level, used capacity index	GLS
Johnstone (2010)	Patents	Political index (built from electric power rates, REC, incentives to research, taxes, managed prices, etc.), R&D, power consumption, electricity prices, EPO patent applications of all technologies	Maximum likelihood (FE) negative binomial
Kneller (2012)	R&D, Capital expenditures (environmental and total)	Environmental operations expenditures, pollution control expenditures at the end of the value chain, value added, business concentration share, payment to skilled workers in relation to the added value and commercial openness index.	GMM
Rubashkina et al. (2015)	R&D, patents and TFP	PACE, added value, government expenditure in R&D, R&D stock, patents stock, export intensity, import penetration ratio, birth and death of companies	2SLS and IV-GMM