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S.S.D.: SECSGP/01–Economia Politica

Environmental Policy Stringency: Measurement and Effects

Tesi di Dottorato di: Rubashkina Yana
Matricola: 3808318

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Exploring relations between environmental regulation and competitiveness: Literature Review

Abstract

This article offers a critical review of the large empirical literature on the Porter Hypothesis (PH). The empirical studies usually investigated the "weak" and the "strong" version of the PH in isolation, not verifying explicitly a channel through which environmental regulation affects economic performance and competitiveness. Furthermore, the issue complicating empirical investigation of the Porter Hypothesis is measurement of environmental regulation, simultaneity between environmental regulation, innovation and competitiveness, as well as unobserved heterogeneity that could bias estimated effect of environmental regulation. With the exception of several recent papers, this issue left unexplored in the literature.

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1 Introduction

This paper summarises theoretical and empirical studies investigating relations between environmental regulation and competitiveness. The level and stringency of environmental regulation has continued to increase steadily worldwide since the early 1970s as environmental quality has assumed growing importance on both the political and public agenda. The issue therefore has become a very hot topic in the recent environmental literature. In light of considerable enforcement of environmental policies in the last decades, the gross costs associated with meeting environmental regulation are very high and of growing concern. Many worry that environmental regulation will place an excessive burden on industrial enterprises, thereby stifling growth and damaging their competitiveness in an increasingly global market place.

There are two main views on an effect generated by environmental regulation on comparative advantages. One view is that environmental regulation raises the costs to firms and imposes constraints on industrial behaviour, hence affecting competitiveness adversely. Environmental regulation forces firms to invest in R&D in cleaner technology. Consequently it displaces R&D expenditure in other more profitable areas such as the firm's core business, given that firm's investment budgets are limited (Gray and Shadbegian, 1993).

An alternative view, known as The Porter Hypothesis (hereafter PH, Porter, 1991; Porter and Van der Linde, 1995), challenges the negative impact of environmental regulation and argues that well-established environmental policy could benefit both the environment and the firm, by making it realise otherwise neglected investment opportunities. According to the PH, stringent environmental policy could result in a "win-win" situation of better environmental quality and higher firms' productivity. The firms, faced with higher abatement costs, would invest in innovation activities to find new ways to meet new regulatory requirements: the resulting production processes and product specification would reduce pollution and, at the same time, lower production costs or increase product market value.

Environmental regulation could stimulate the firm faced with market imperfections, such as imperfect information, organisational inertia or control problems, to introduce innovation, that, in turn, helps to increase resource efficiency and enhance productivity. Compliance costs could be consequently offset, and the firm would get a competitive advantage in the foreign countries, not subject to similar regulation.

Initially formulated in rather general terms, the PH can be declined as three possible and distinct research statements (Jaffe and Palmer, 1997). First, the "narrow" version of the PH postulates that flexible environmental regulation, such as market-based instruments, increases firmsncentives to innovate compared to prescriptive regulation, such as performance-based or technology-based standards. Second, the "weak" version of the PH postulates the positive effect of well-crafted environmental regulations on environmental innovations (even when environmental innovation comes at an opportunity cost that exceeds its benefits for a firm). Finally, the "strong" PH states that innovation induced by well-crafted environmental regulation could more than offset additional regulatory costs, and, consequently, increase firm competitiveness and productivity.

The objective of this paper is to bring together two detached research lines, namely "weak" and"strong" PH, and summarize theoretical and empirical evidence on the relation between environmental regulation and competitiveness. We illustrate several potential problems and biases that arise when the relations are investigated in isolation. We discuss different environmental policy indicators commonly used in the literature and their shortcomings. Furthermore, we identify potential gaps for further research. The paper proceeds as follows. Section 2 briefly summarizes the theoretical literature on the PH. Section 3 discusses different components of competitiveness relevant for empirical investigation of the PH and overview empirical papers investigating impact of environmental regulation on each indicator in turn. Section 4 summarises various environmental regulation indicators commonly used in the literature. Finally, Section 5 discuss potential identification problems arising in the econometric investigation of the PH.

2 Theoretical literature

Porter, 1991 and Porter and van der Linde, 1995 provide anecdotical evidence based on the case studies that "innovations offsets on environmental regulation are common" (Porter and van der Linde 1995). The idea was later formalised in the firm-level theoretical models, that can be broadly divided into two types: the inter-firms models where environmental regulation could be beneficial for firms, correcting for market failure (Xepapadeas et al.,1999; Simpson and Bradford, 1996; Alpay, 2001) and the intra-firm models obtaining results in the context of organizational failure (Andre et al., 2009).

The inter-firms models assume the existence of a market failure[1] under which environmental regulation could improve both firms performance and environmental quality. In this vein, Xepapadeas et al.,1999 suggest a theoretical model that looks at firms‘ reaction with respect to both the type and the quantity of equipment in which they invest in response to changes in the production costs due to environmental tax increase. They found that environmental tax increase reduces the total capital stock (so-called "downsizing effect"). Under special condition on parameters the "downsizing" of the firm also causes modernization of capital stock (a decrease in the average age of capital stock), which, in turn, increases the average productivity of the firm. They conclude that under assump-

[1] Market failure happens when the allocation of goods and services by a free market is not efficient. That is, there exists another conceivable outcome where a market participant may be made better-off without making someone else worse-off.

tion of some functional form for a relatively narrow sub-set of parameter values when the downsizing of the home industry due to a stricter environmental policy is accompanied by modernization of its capital stock, there are smaller losses in profits and there are greater gains in emission reductions relative to the case where modernization is not possible (Xepapadeas et al.1999). However, their results suggest that even when environmental regulation mitigates the conflict between environmental quality and competitiveness, it would not be likely to yield a "win-win" situation.

Simpson and Bradford, 1996 evaluate Porter argument in a strategic trade model, with the domestic and foreign firms producing perfectly substitutable goods and the domestic government introducing the effluent tax. Differently from the other authors they introduce in the model R&D spillovers, reflecting that a firm may be unable fully to appropriate all gains accruing to its own innovative activity as R&D expenditure could reduce not only its own cost, but also the rival's cost. It comes out from the model that innovation spillovers are likely to be an important consideration in analysing the effects of effluent taxes on domestic R&D, and, consequently, on domestic firm profits as it decrease the domestic firm‘s innovation offset effect. The authors conclude that domestic effluent tax hinges on its net effect on foreign cost-reducing investment, a factor the domestic authorities cannot regulate directly and may find difficult even to predict with any confidence (Simpson and Bradford 1996).To summarize, the authors are skeptical about the Porter results saying that "..it may be a theoretical possibility, but that it is extremely dubious as practical advice" (Simpson and Bradford 1996).

In an open economy model with two countries, each accommodating two Cournot-oligopolists producing a good, Alpay, 2001 investigates how tradable emission permits affect international competitiveness. The paper develops the mechanism where due to change in tradable emission permit's prices and price elasticity of demand environmental regulation makes some non-feasible R&D projects profitable, consequently enhancing international competitiveness of the firm. Higher environmental standards at home increase demand for domestic production and open up a new channel towards increased competitiveness (Alpay, 2001). Conditional on parameters the results are in accordance with the Porter hypothesis.

Similar idea stemming from consumer preferences, is suggested in the paper of Andre et al., 2009. In a strategic duopoly model under imperfect competition and differentiated products, environmental policy solves firms coordination failure problem. In an unregulated case the game could result in a classical prisoner dilemma, where both firms produce a standard variant of the good, but stand to benefit from a joint decision to produce a more environmentally friendly variant. They show that consumer preferences, rather than any productivity gain or cost savings brought about by regulation may favour creation of a regulated environment, in which firms stand to benefit from sales of higher quality products at higher prices. Consumers are often willing to pay more for a cleaner product, but the firm adopting a new technology to produce the cleaner product under the unregulated market potentially expose it to the opportunistic behavior of its competitors (which could then go on to market the cheaper, low quality good at a lower price, thereby capturing a large share of the market). Differently, under the regulated market an innovative firm will benefit as also competitors are forced to produce the "green" products, it reduces price elasticity of demand and there is no risk of price disadvantage.

In a stylized model of intra-firm renegotiation between a firm owner, a manager and an environmental regulator, Ambec and Barla, 2002 address the issue of environmental policy correcting organisational failure. The paper suggests the mechanism where regulation creates external pressure to overcome organizational inertia. The managers in the model have private information about an outcome of R&D investments. In order to favour revelation by the agents, the shareholders must offer informational rent when a successful R&D program is reported. As this rent is a cost for the shareholder, it lowers incentives to invest in R&D. The model shows that environmental regulation reduces the informational rent, thereby increasing investments. Nevertheless, the PH is confirmed only for the specific parameters value.

3 Empirical literature

In this section we discuss the empirical framework commonly used in the literature studying the link between environmental regulation and competitiveness.

Notion of "competitiveness" includes multiplicity of issues. According to Porter's definition, competitiveness is a superior productivity in terms of lower costs or ability to offer a product with a superior value that justify a premium price. (Porter, 1991). An alternative definition of competitiveness is ability of an industry or a sector to sell cheaper or better quality goods and services in both local and international markets (Peterson, 2003). Capacity to innovate and upgrade is the main prerequisite of international competitiveness. Thus, the key questions related to investigation of environmental regulation impact on competitiveness are likely to involve consideration of the following:

- Impact on plants survivorship;
- Impact on innovation;
- Impact on productivity;
- Impact on export behaviour;
- Impact on financial performance;
- Impact on production location of pollution-intensive goods and services.

Manufacturing enterprises usually become a focus of the PH analysis, as on the one hand, they are more likely to be disproportionately affected by environmental regulation, and on the other hand, they can relocate to other countries with less stringent environmental standard (Jaffe et al., 1995).

The link between environmental regulation and each component of competitiveness has been a subject of vast empirical analyses which, however, usually were carried out in isolation. The relations are commonly investigated in a reduced-form model:

$$C = f(ER, Z) \tag{1}$$

where C is competitiveness indicator;
ER is environmental regulation indicator;
Z are other controls.

For instance, in the context of “weak" PH, numerous studies address environmental innovation response to environmental regulation (e.g. Brunnermeier and Cohen, 2003; De Vries and Withagen, 2005; Johnstone et al., 2010). Although they commonly find that environmental regulation stimulates certain kind of environmental innovation, there is no guarantee that the direction or rate of this increased innovation is socially beneficial. In other words, these studies do not consider the opportunity costs of environmental innovation, and could not tell how regulation affect overall performance and international competitiveness of manufacturing sectors.

In contrast, many studies proving the “strong" PH use productivity measure (e.g. Gray and Shadbegian, 1993, 2001; Lanoie et al., 2008), export measure (e.g.Costantini and Mazzanti, 2011) or financial measures (e.g. Rassier and Earnhart, 2009) as a competitiveness indicator. The evidence obtained from these studies are mixed, with uncertain implications for productivity, export activity and financial performance.

The drawback of the above mentioned studies investigating on the “strong" PH, is that focusing on a particular aspect of competitiveness in a reduced-form model they did not reveal a specific channel through which environmental regulation affects competitiveness. To understand the mechanism that underlies the relations several paper used a combined assessment and looked at the impact of environmental regulation on both innovation and financial performance (e.g. Rennings and Rammer, 2011). These papers estimated a set of reduced-form equations (one by one) where innovation and financial performance is a function of environmental regulation and other controls. There are also a few papers that apply a sequential procedure and studied the link between environmental regulation and innovation at the first stage, and then at the second stage investigated the effect of regulation induced-innovation, if any, on productivity (e.g. Hamamoto, 2006; Yang et al., 2012).

The PH has been investigated at different level of data aggregation. Surely, the most relevant level of data aggregation for investigation of competitiveness is by industry or by firm. As stressed by Porter, regardless of striking differences in patterns of competitiveness in every country, no nation can be competitive in every or even most industries (Porter, 1990).The firm level evidence used by Porter to support his idea results from the case studies rather than econometric investigations. Constrained with the data availability for the econometric analysis, subsequent papers extend the investigation of the PH a the firm-, sector-, industry- and country-levels.

In the following we review selected empirical papers addressing the PH. We summarise the main variables, the data and relations derived in these papers in Tables 1-6 .

3.1 Innovation studies

According to the PH, in response to stringent environmental regulation a firm could introduce innovation that addresses environmental impact, while improving product and/or related process. The "product offset" occurs when environmental regulation produces better performing or higher quality good, safer product, lower product cost. The "process offset" occurs when environmental regulation results in improved resource productivity, higher process yields or material savings.

Previous studies of the “weak” PH, investigated the effect of environmental regulation on green innovation proxied by relevant patents or R&D expenditure. For instance, Brunnermeier and Cohen, 2003 investigate the impact of increasing pollution expenditures on number of environmental patent applications by US manufacturing industries in the period of 1983 -1992. The paper confirmed the positive impact of environmental policy on environmental patents.

In a cross-country setting De Vries and Withagen, 2005 focused on investigation of the environmental policy effects on innovation related to SO2 abatement in twelve European countries, the US and Canada over the period 1970-2000. The strictness of environmental policy is captured by different proxies such as dummy variables of international agreements on SO2 reduction (the agreement covers all countries under consideration, therefore the policy variable is country-invariant) or environmental sensitivity performance index (that is different across countries, but constant over time). Using these indicators the paper concluded that innovation do not have a significant relationship with environmental regulation stringency. Alternatively, the paper considered the environmental regulation as a latent variable that is contingent on gross domestic product, the industry structure and the level of SO2 emissions. With the latter approach the paper found an evidence that strict environmental regulation induces new SO2 abatement technologies.

Johnstone et al., 2010 examined the effect of renewable energy policies, proxied by various environmental policy adoption dummies or a composite policy variable constructed using principal component analysis, on technological innovation. The analysis is conducted using patent data in each of the technological areas of renewable energy (wind, solar, geothermal, ocean, biomass, and waste) of 25 OECD countries over the period 1978-2003.The paper found that public policy plays a significant role in determining renewable energy patent applications. The other major policy-related finding of this paper is that different policies have a greater effect on patent activity for some renewable energy sources than for others. In particular, quantity- based policy instruments such as obligations and tradable certificates are most effective in inducing innovations in wind power technology. Price-based instruments such as investment incentives, tax measures and tariffs are most effective in encouraging innovation in solar, biomass, and waste-to-energy technologies. Voluntary programs are not significant, except n the case of waste. These findings are robust to alternative policy measures and model specifications.

The studies linking environmental regulation stringency with green innovation are numerous, but due to the lack of green innovation data by sector the "weak" PH is usually investigated at the aggregate country level. However, as mentioned earlier in the paper, sector-level studies could be more appropriate in this context with respect to a country-level analysis as the earlier better capture the sector-specific environmental policies effect and dynamics of competition that takes place within a sector. Moreover, while generally concluding that environmental innovation positively responds to environmental policy, these studies do not consider the opportunity costs of environmental innovation and crowding out of innovation in the core business.

Several papers studied how environmental regulation affect on overall (environmental and non-environmental) innovation at the sectoral-level. Jaffe and Palmer, 1997 analysed the relationship between stringency of environmental regulation, measured by environmental regulatory compliance capital costs, and overall innovative activity in the US manufacturing sectors over the period 1975-1991. Overall, the authors found a mixed evidence with respect to the hypothesis that increased stringency of environmental regulation spurs increased innovative activity by firms. In particular, they found a significant positive link between sector-level of compliance costs and overall R&D expenditures. However, no impact is confirmed for overall patents.

A similar framework and environmental regulation proxy were used for the number of other countries. Hamamoto, 2006 estimated the R&D expenditures effect of environmental regulation for Japanese sectors over the period 1972-1982 and Yang et. al, 2012 - for Taiwanese sectors over the period 1997-2003. Both papers showed that the pollution control expenditures have a positive relationship with the R&D.

Kneller and Manderson, 2011 addressed the issue of opportunity costs of environmental regulation and crowd out effect of non-environmental innovation, using sector-level data from UK manufacturing industry during 2000-2006. The paper used pollution abatement costs as a policy proxy and accounted for its likely endogeneity using the lags of endogenous variables as instruments. The results indicated that while environmental

R&D and investment in environmental capital are stimulated by greater pollution abatement pressures there is no positive impact of environmental regulation on total R&D or total capital accumulation. Therefore, the authors concluded that environmental R&D crowds out non-environmental R&D. Still, there did not confirm that environmental capital crowds out non-environmental capital.

3.2 Survivorship studies

As well-know from the standard economics theory, it is optimal for a firm to close or exit from the market, if its scrap-value exceeds the expected discounted profit of not exiting at this time. It is also well-established in the empirical literature that productivity and exit probability are negatively correlated (e.g. Syverson, 2011). Therefore, to estimate the impact of environmental actions on firms economic performance exit behaviour is sometimes concerned, measured by conditional exit probability of a firm under environmental regulation.

Greenstone et al., 2012 investigated exit behaviour and productivity response to air quality regulation of the US plants belonging to different manufacturing sectors in the period of 1972-1993. The authors found a mixed evidence on air regulation effect on firm's exit behaviour. In particular, plants in heavy-emitting industries are found to to have higher exit probability when their county is a subject to ozone regulation. On the contrary, several policies such as carbon monoxide and total suspended particulate regulation are proved to bring a positive effect on survivorship.

Yin et al., 2007 explored the reasons why some petroleum retail outlets in the US are more likely to exit the market than others under the Underground Storage Tank (UST) regulation introduced in the early 1980s. The major conclusion of the paper is that environmental regulation has an uneven impact on different types of petroleum outlets. Small outlets have greater difficulties in dealing with environmental regulation if compliance cost is significant and are more likely to exit the market than bigger outlets. The reason is that economies of scale provide large facilities with a competitive advantage because it is more difficult for small facilities to pass on compliance costs to their customers. Liquidity constraints make small outlets more vulnerable to environmental regulation due to lack of the financial capability to meet regulatory requirements.

The relations between environmental regulation and probability to shut down are investigated mostly for the US, while the evidence for the other countries is scant. One of the few papers that focuses on exit behaviour of the European firms under stringent environmental regulation is a paper of Biørn, 1998. This paper compared the exit probability of regulated and non-regulated establishments in Norwegian manufacturing industries, focusing on three highly regulated sectors such as pulp and paper, iron, steel and ferroalloys sectors, over the period 1976-1991. The regulation under consideration imposed restriction on annual emission quantities and/or maximum concentrations (quantity per unit of volume). They authors concluded that non-regulated establishments had, ceteris paribus, a higher exit probability than regulated establishments.

To summarise, due to lack of relevant data the impact of environmental regulation on exit probability is less investigated. Further research employing cross-country data would be required to get better understanding of the relations in this respect.

3.3 Productivity studies

The link between environmental regulation and productivity is the most relevant, as well as the most controversial issue related to "strong" PH investigation. Since the 1980s a large body of literature attempts to quantify the effect of environmental regulation on productivity at the plant-level for the US. The common conclusion of the earlier investigations is that environmental regulation has an adverse effect on productivity in the US. For instance, Gray and Shadbegian, 1993, 2001 investigated the link between environmental policy stringency, measured by pollution abatement and control expenditures, and plant-level TFP of the paper, oil, and steel industries in the US over the period 1979-1985. The authors concluded that environmental regulation caused a productivity slowdown due to displacement of "productive" investment by environmental innovation.

Greenstone et al., 2012 estimated the effect of the Clean Air regulation on plants' TFP levels in the US in the period of 1972-1993. They found that among surviving polluting plants, a more stringent regulation is commonly associated with a TFP decline. The regulations governing ozone have particularly discernible effects on productivity, though effects are also seen among particulates and sulfur dioxide emitters. On the contrary, carbon monoxide regulation appears to increase measured TFP, though this appears to be concentrated among refineries.

Berman and Bui, 1999 examined the effect of regional air pollution regulation on the productivity of oil refineries (one of the most regulated industries) in California in the period 1979-1992. The authors proxied environmental regulation stringency with a count of active regulations in each particular industry and year. The paper found econometric evidence that regulation induced large investment in air pollution abatement capital, that, in turn, enhanced productivity.

As far as the investigation of the other countries is concerned, the sector-level analytical framework has been commonly applied. Lanoie et al., 2008 focused on productivity effects of environmental regulation, proxied by share of abatement and control investment in total cost, in the Quebec manufacturing sectors in the period 1985-1994. The paper found the negative productivity effect in the short-run. However, the effect turned to be positive for less polluting industries in the long-run. On the contrary, the productivity of more polluting industries declines in the long-run period.

Despite of extensive studies of productivity response to regulation for the US, there are a few papers, employing the productivity indicator in the context of PH studies for Europe. One of the very few papers related to Europe, is Marin and Lotti 2014 who studied the impact of environmental patents (together with non-environmental patents) on productivity of the Italian manufacturing firms in the period 1995-2006 at the firm-level . The paper concluded that environmental patents have strong positive effects on productivity. However, they exhibit a lower return relative to other innovations, at least in the short run, with the differential effect being more pronounced for polluting firms.

It worth noting that in a sector- or a country-level model estimated productivity or trade effect is conditional on plants survivorship. Stringent regulation could result in plants closing, as well as affect aggregate productivity and trade indicators. Not accounting for survivorship in a sector- or a country-level model the true impact of environmental regulation on productivity and international trade could be understated.

3.4 Trade studies

According to the trade theory, countries export those goods and services that they make relatively more efficiently than other nations, and import those goods and services that are relatively less efficient at producing. Hence, the effect of environmental policy on competitiveness could be measured by identifying the effect that it would have on net exports. [2]

Tobey, 1990 and 1993 was the first to investigate econometrically relation between environmental policy, proxied by pollution abatement capital expenditure, and international trade in a multi-country framework. The papers examined the impact of omitting the environmental policy stringency indicator on multilateral trade flow using the "Heckscher-Ohlin-Vanek model". The results don't confirm the causal relations between environmental policy and international trade. Similarly, the other earlier trade studies commonly conclude that environmental regulation has a negligible or even negative effect on export.

There is a limitation of using multilateral trade flow as a dependent variable when studying environmental policy-trade relations, as differential effects of environmental policy on various trade flows may cancel out due to aggregation. Thus, more recent studies use the "gravity model" approach and employ a bilateral trade flow as a dependent variable (e.g. Van Beers and Van den Bergh, 2000; Costantini and Crespi, 2008; Costantini and Mazzanti 2011). These papers find a mixed evidence in support of the "strong" PH.

[2] The theoretically required condition would be to hold real wages and exchange rates constant, so as to be sure, that it is not relative labour cost or exchange rate shift that drive the net export (Jaffe et al., 1995). However, the data are not easily available, so it is difficult from empirical point of view to include these controls into export equations. Due to unavailability of the perfect indicator net from the above mentioned adjustments, the net export is widely used as a proxy of competitiveness.

For instance, Van Beers and Van den Bergh, 2000 performed a gravity analysis with the 1975 data employed by Tobey, for five dirty sectors, and a country sample similar to Tobey's. The environmental regulation in this paper is proxied by the self-reporting score of a country's perceived stringency obtained from the questionnaire. The authors confirmed a positive impact of environmental policy on international export in paper industry. However, no relations are found for chemical and steel industry, and negative relations are derived for mining and non-ferrous metals.

Using the panel of OECD countries in the period 1996 - 2005, Costantini and Crespi, 2008 focused on the energy sector and looked at the impact of CO2 emission and environmental tax on export of environmental technologies of this sector. The authors found the evidence supporting the "weak" PH. They concluded that countries with stringent environmental standards have a higher export capacity for those environmental-friendly technologies that regulation induces to adopt.

Investigated the "strong" PH, Costantini and Mazzanti 2011 studied export behaviour of different manufacturing sectors under stringent environmental regulation in 15 European countries in the period 1996-2007. Environmental regulation is measured by different indicators such as energy and environmental tax revenues as percentage of total revenues, pollution abatement and control expenditures as percentage of GDP and number of eco-management and audit scheme initiatives by private firms as percentage of GDP. Divergent effects played by different policies are ascertained, demonstrating that the PH is not to be taken for granted and it is sector-specific, as well as policy instrument-specific. Overall, picture is nevertheless largely in favour of positive effects of environmental policies on the EU competitiveness. In particular, the high tech sector is the one that responds more positively to energy and environmental taxation. However, the paper did not find any effect when using pollution abatement and control expenditures and number of eco-management and audit scheme initiatives by private firms as environmental regulation proxy.

All in all, trade studies designed to test the PH hypothesis have shown so far a mixed evidence.

3.5 Financial studies

Number of recent empirical papers assessed the strong version of the Porter Hypothesis examining the impact of environmental regulation on firms' financial performance. These paper usually use the cross-section firm-level framework. As a measure of financial performance they commonly use return on sales, return on assets (e.g. Russo and Fouts, 1997), Tobins q (Konar and Cohen, 2001; Rassier and Earnhart, 2009) or firm‘s price cost margin (Rennings and Rammer, 2011). Return on sales or return on assets is an accounting-based measures of financial performance that indicates how effectively a firm is utilizing its resources to generate profits. Tobins q is a market-based measure, that reflects investors expectations of the discounted present value of future profits. It is defined as a ratio of a firms market value to the replacement cost of the firms assets.

As far as Tobin‘s q is concerned, Rassier and Earnhart, 2009 investigated whether a more stringent Clean Water regulation in the US limits an expected Tobin q and undermines future financial performance of the US firms in the period of 1995-1997. By decomposing Tobin q into its constituent components, such as market value and replacement costs, and estimating each component separately, they found that tighter permitted discharge limits lower both components with a larger impact on market value, which implies that investors revise their expectations of the discounted present value of future profits in response to a more stringent Clean Water regulation.

In a cross-section framework Rennings and Rammer, 2011 studied impact of different environmental policies on price cost margin (computed as a share of sales net of input cost in total sales) of German firms in the period 2000-2002 using the data from German Innovation Panel. They found that process innovations exert a negative impact on firms price cost margin, while product innovations motivated by some type of environmental policy, such as regulation on recycling, waste management or resource efficiency, result in a positive profitability impact. The authors sum up saying "..environmental innovations on average do not perform worse compared to other innovations...However, if we look at specific environmental policy fields, we find winners and losers of environmental policy" (Rennings and Rammer 2011).

A common limitation of financial studies is that (with the exception of the US) due to lack of data availability, they rely on a single observation year and a single country, which naturally restricts a generalisation of the results. Longitudinal data would certainly be helpful in order to learn more about the time dimension between environmental regulation and financial performance.

3.6 Combined assessment

The drawback of the studies discussed so far is that investigating the "weak“ or the "strong“ proposition of the PH in isolation they do not reveal a true mechanism through which environmental regulation affects, if any, productivity, financial performance and export behaviour. There is a conflicting view on effect generated by environmental regulation on comparative advantages, known as the Polution Heaven Hypothesis (hereafter PHH, Copeland and Taylor, 1995). In the context of trade liberalisation in developing countries, it states that being a subject to strict regulation, a firm either contract production to foreign manufacturing firms (outsourcing) or invest in foreign manufacturing facilities and produce abroad. [3] In light of the alternative perspectives, an analysis that

[3] See Brunnermeier and Levinson, 2004 for the literature review of Pollution Haven Hypothesis.

disentangle the mechanism by which firms respond to environmental regulation is of high relevance.

To address this issue several papers provided a sequential estimation and studied at the first step the link between environmental regulation and innovation, and then at the second step, the link between induced innovation, if any, and productivity. Hamamoto, 2006 estimated an impact of regulation on R&D and capital modernisation of manufacturing sectors in Japan. Having showed that the pollution control expenditures have a positive relationship with R&D and a negative relationship with the average age of capital stock, the paper further estimated how induced R&D and change in the average age of capital stock affect productivity. The paper concluded that R&D increase stimulated by the regulatory stringency have a positive effect on productivity growth, whereas the effect of changes in the average age of capital stock is insignificant. In a similar framework Yang et al., 2012 examined whether stringent environmental regulation induce more R&D and promote further productivity in Taiwan in the period 1997-2003. The finding supports both the "weak" and the "strong" Porter hypothesis.

Several recent papers addressing the "strong" PH at the firm-level, directly introduced the variable of induced innovation in the model and compared its economic effect with the effect of the other innovations (e.g. Rennings and Rammer, 2011; Marin et al. 2014). The induced innovation variable is constructed from the survey that asked firms to report innovations triggered by environmental regulation. Using the German data, Rennings and Rammer, 2011 investigated if firms with induced innovations achieved similar innovation success and the level of profit (proxied by price-cost margin) as the other (non-environmental) innovators. The paper found a negative impact of induced innovation on the probability to introduce market novelties, and no impact on the share of sales generated by market novelties within the group of firms that introduced similar innovation. Moreover, induced environmental process innovation found to yield a lower price-cost margin, whereas product innovation triggered by resource efficiency regulation is found to increase firm profitability. In a similar framework, Marin and Lotti, 2014 studied the impact of induced patents and other patents on productivity of Italian manufacturing firms. The paper concluded that environmental patents have strong positive effects on productivity. However, they exhibit a lower return relative to other innovations, at least in the short run, with the differential effect being more pronounced for polluting firms.

4 Measures of environmental policy

The issue of measurement of environmental regulation stringency became one of the main challenge of the PH empirical studies. There are several problems related to measurement of environmental policy effort of a country or a sector. First, sophisticated environmental policy design makes an evaluation of overall policy effort problematic. The diversity of policy instruments applied in different countries and change of instruments composition over time hamper comparability across countries and over time. There appears to be quite wide general consensus on the importance of using multiple policy instruments in order to address the variable barriers for environmental efficiency. Typical policies that target industrial environmental performance include regulations and voluntary agreements that directly compel actions; economic policy instruments such as taxes and tax incentives, directed financial support (e.g. subsidies and loans) and differentiated energy prices that seek to influence the cost effectiveness of technical actions; and informational policies, which help improve information provision for companies and establish a favourable environment to implement environmental actions (Reinaud and Goldberg 2011). Second, there is a limited availability of data that allow to construct time-variant indicator of environmental regulation. Furthermore, as stringency of environmental regulation is a multidimensional notion, a general incompleteness of all available stringency indicators is related to inability to capture some important aspects of environmental regulation such as sophistication of regulatory structure, strictness of enforcement, quality of environmental institutions and of available environmental information, subsidisation of natural resources. Unfortunately, the data on these aspects of regulation are generally unavailable.

Various environmental regulation indicators, summarised in Table 7, were employed in the empirical investigations, however subject to numerous drawbacks. In the following section we discuss each indicator, in turn.

4.1 Single policy indicators

The empirical literature often studies how specific environmental policy affect competitiveness. For example, several studies investigate impact of environmental taxation, increasingly favoured recently by the EU countries (Constantini and Crespi 2007, Constantini and Mazzanti, 2011). An environmental tax is a tax whose tax base is a physical unit that has a proven specific negative effect on the environment. The tax includes energy taxes, transport taxes, pollution taxes and resource taxes. In the context of the PH studies environmental tax is usually proxied by environmental tax revenue share in total government revenue. However, low revenue from environmental taxes could reflect higher tax rate that have had the effect of changing behavioural patterns. Therefore, a more appropriate indicator is the one that adjusts the environmental tax revenues by a corresponding aggregate tax base. As far as energy tax is concerned, implicit tax rate calculated as energy tax revenue in relation to final energy consumption, could be a better proxy of energy tax rate. However this indicator has not been yet exploited in the PH studies.

Another commonly used proxies are policy adoption dummies. Various policies such as international environmental protocols, environmental taxes, investment incentives, differentiated tariffs, voluntary programs, government support of green R&D are proxied in the econometric model in this way (e.g. De Vries and Withagen, 2005; Johnstone et al., 2010). The advantage of this approach is that dummy variables are easy to construct. However, their serious drawback that they do not tell about regulation stringency. Moreover, dummy variables could mistakenly capture effects not related to regulation (e.g. related to time trends). Furthermore, Including all policy dummies may cause multicollinearity. At the same time, including policy dummies one-by-one may lead to incorrect conclusions due to omitted variables and possible interaction effects among the different policies.

All in all, a complex policy design makes an evaluation of a single policy problematic. Recent environmental policy consists of combination of programs, rather then a single policy. Controlling for a single policy in an econometric model could result in omitted variable bias.

4.2 Aggregate indicators

Taking into account the above-mentioned, many authors investigate the impact of overall rigour of various regulation, rather than a single policy. An aggregate environmental regulation indicators used in these studies could be divided into four broad groups: measure of compliance costs, composite indicators, indirect measure of emission levels and indirect measures of induced innovation. Popular proxies for regulatory stringency are data on private sector abatement expenditures. Such data inform on the level of financial effort a given firm/sector has to face to comply with given standards (Jaffe and Palmer, 1997; Gray and Shadbegian, 2001; Berman and Bui, 2001; Hamamoto, 2006). Pollution abatement and control (PAC) activities are purposeful activities aimed directly at the prevention, reduction and elimination of pollution or nuisances arising as a residual of production processes or the consumption of goods and services (OECD 1996). PACE are consequence of government environmental policies and regulations and comprises the flow of investment and current expenditure that is directly aimed at pollution abatement and control. The justification of this indicator is based on the assumption that profit maximising firms typically face marginal abatement costs that are increasing in pollution abatement. However, pollution abatement costs (PACs) are plagued with reverse causality and endogeneity issues that we discuss in the next section.

Another popular measure of environmental policies is emission or energy use intensity (e.g. De Vries and Withagen, 2005; Constantini and Crespi, 2008). Indeed, these measure captures only the policies addressing emission reduction. However, its interpretation differs from one study to another. Lower CO2 emission is the evidence of applying stringent (and efficient) environmental regulation and higher effort regarding Kyoto abatement targets. Whereas De Vries and Withagen, 2005 treat emissions variable other way round, saying that if a country has a relatively high level of SO2 emissions, environmental stringency in that country will be relatively more intense. Besides the ambiguous assumption behind this measure, emissions intensity suffers from the endogeneity, as it is determined by economic performance. Aggregated over firms or sectors, these variables are also likely to mirror changes such as factor prices rather than regulatory stringency. When they are used at the disaggregated level, it is often hard to build indicators that can be used in cross sectoral or cross country analysis due to the heterogeneity of the regulated pollutants.

Several papers used qualitative indicators such as Index of Environmental Sensitivity Performance as a proxy of overall environmental regulation (De Vries and Withagen, 2005). The data used to this end include information on the presence or absence of a given policy (0-1 indicators) or scores from surveys of government officials or business leaders (Tobey, 1990; Kellenberg, 2009). Moreover, the composite indicators are usually time-invariant, and, therefore, do not allow to track environmental regulation effect over time.

Several recent papers developed a time-variant composite indicator of renewable energy policies across European countries (Johnstone et al. 2010; Vona and Nicolli, 2012). As the indicators focus on the renewable energy policy that barely affects manufacturing enterprises, the scope of application of these indicators in the PH context is naturally restricted.

4.3 Endogeneity and simultaneity

The issue complicating investigation of environmental regulation effect on competitiveness in an econometric model is causal relationships running in both directions. There are several reasons why causation could run from competitiveness to environmental regulation. Firstly, when using pollution abatement expenditures as a policy measure, they could be simultaneously determined with innovation. Induced innovation designed to lower costs of compliance could decrease pollution abatement expenditures. Secondly, in the financial studies financial performance could be simultaneously determined with environmental regulation. According to political-economy models in order to maximize political support, regulators may impose regulation that is inversely related to a firm financial performance. In this case financial performance could affect environmental regulation. Thirdly, simultaneity could arise at the sector- or country-level studies because increased productivity and international trade could leads to higher per capita income, that, in turn, could result in to greater demand for environmental quality. Environmental regulations could thus be a function of economic performance and international trade.

Another problem that could bias environmental regulation effect in the econometric model addressing the PH, in particular at the sector- or country-level, is unobserved heterogeneity. Unobserved attributes determining economic performance, could be correlated with environmental regulatory stringency. If the data is used at the aggregated level, such as sectors or countries, changes in PACs might result from changes due to unobserved heterogeneity rather than from changes in regulatory stringency. Like, high compliance costs could indicate an ineffective response (due to low level of expertise in dealing with environmental regulation or to low productivity efficiency) instead of high levels of stringency. Moreover, a low level of compliance costs does not necessarily mean that a country is not effectively protecting its environment. In fact, the indicator tends to emphasis clean-up costs at the expense of cost reductions which could be due to reduced emissions or more effective protection measures. Alternatively, extremely severe regulations might cause many plants to close down, leading to measured compliance costs being low rather than high (Jaffe et al. ,1997). Finally, in the presence of market of behavioral failues abatement expenditures no longer successfully measure the level of regulatory pressure (Berman and Bui, 2001). In the context of environmental regulation-export linkage, another source of omitted variable bias is export rebates and import surcharges, that usually could not be controlled for due to data unavailability. As highlighted by Van Beers and Van den Bergh, 2000 there is a possibility that the country spending a substantial part of its financial resources to abate pollution may also provides financial assistance as a compensation for increased production costs to pollution cost-sensitive industries. Not controlling for it in the model, may produce overestimation of the regulation effect.

In the presence of the omitted variable bias, application of panel data models has an advantage of allowing to control for unobserved heterogeneity as long as it is assumed to be time-invariant. What concerns the simultaneity problem it could be addressed employing an instrumental variable approach that account for the simultaneity of environmental policy, like for example it is done in the papers investigating the PHH of Ederington and Minier, 2003, Levinson and Taylor, 2003, and Xing and Kolstad, 2002. Moreover, proper treatment of a lag structure reduce the simultaneity problem. The existing literature does not explicitly account for these two-way causal relations with the exception of Kneller and Manderson, 2012.

Apparently, to avoid some of the above discussed biases it would be preferable to use a measure that reflect government's effort towards environmental regulations, rather then response indicators like PACE, that capture regulation compliance costs, or emission intensity, that capture regulations results and effectiveness. Unfortunately, a reliable aggregate measure that captures government effort, rather then outcomes of environmental regulation is not available.

4.4 Dynamic effect

Finally, an important issue in the empirical setting of the PH the dynamic effect of environmental regulation. Many studies look at the contemporaneous effect of environmental regulation. However, innovations might take several years to develop, and capital expenditures are often delayed for a few years through normal budgetary cycles and building lags (Jaffe and Palmer, 1997, Lanoie et al, 2008, Ambec et.al 2011). Therefore, environmental regulation adopted today will affect firms performance a few years down the road when the innovation process and/or changes in production will have been completed. For this reason it is important to allow for one or more lags in the environmental regulation variable.

5 Conclusions

This paper offers a critical review of the large empirical literature on the Porter Hypothesis (PH) investigating the relations between environmental regulation and competitiveness. According to the PH, stringent environmental policy could result in a in-winituation of better environmental quality and higher firmsroductivity and international competitiveness. Though the argument has been long debated in the literature, the evidence obtained so far still remains inconclusive. The literature often supports the "weak" PH confirming positive impact of environmental regulation on green innovation. However, the studies focusing on environmental innovation effect, usually do not consider the opportunity costs of environmental innovation and potential crowding out of innovation in the core business.

As regards to the "strong" PH, the investigations have not been successful so far in finding robust support of enhanced productivity, export activity and financial performance under environmental regulation. The common drawback of these studies is that they investigated the "weak" and "strong" version of the PH in isolation and therefore, do not explicitly verify a specific channel through which environmental regulation affects economic performance and competitiveness. To reveal the causal links between environmental regulation and competitiveness, implied by the PH, combined assesment of innovation and competitiveness effects is required. In this way one can be sure to identify the true channel of regulation impact. Still, only a few papers follow this approach.

Furthermore, the issue complicating investigation of the PH is measurement of environmental regulation stringency, simultaneity between environmental regulation, innovation and competitiveness and unobserved heterogeneity arising in the econometric model. Failure to take account of this endogeneity problem could lead to a bias estimates of environmental regulation effect. With the exception of several recent papers, this issue left unexplored in the PH literature.

The PH has been investigated at different level of data aggregation such as firm-, sector-, industry- and country-levels. Extensive research on both alternative hypotheses of the PH were carried out for the US, using both plant- and sector-level data, various innovation and competitiveness indicators. In contrast, due to the limited data availability Europe is much less investigated, although the issue of implications of stringent environmental regulation on the firm's competitiveness is of high relevance. In particular, very few papers carried out the cross-country analysis at firm- or sector-level. However, if there is indeed a PH story in the data, it is more likely to be found at the disaggregated level. Moreover, the papers investigating Europe mainly focused on specific new technologies in the environmental goods sector, and left aside very relevant to the propositions of the PH issues of productivity response, financial performance and firm survivorship to stringent environmental regulation. Therefore, we believe there is a gap in the empirical PH literature that needed to be fulfilled as soon as data for European countries become available. This can be a topic for future research.

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Tab. 1: Selected innovation studies of the PH

Study	**Competitiveness indicator**	**Environmental regulation proxy**	**Other controls**	**Sample and level of aggregation**	**Estimated regulation effect**
Jaffe and Palmer, 1997	Patents, R&D expenditures	1-year lagged, 5-years moving avg. PACE	VA, government R&D, foreign patents	U.S. manufacturing sector-level, 1973-1991	**positive** for R&D, **insign** for patents
Brunnermeier and Cohen, 2003	Environmental patents	contemporaneous and 1-2 years lagged PACE, pollution related inspections	Industry shipments value, concentration, capital intensity and export intensity	US manufacturing sector-level, 1983-1992	**positive**
Vries and Withagen, 2005	SO2 reduction related patents	Dummies for the year of international environmental protocols on SO2, time-invariant binary Index of Environmental Sensitivity Performance, SO2 emission level	GDP, people active in R&D, % of industry VA from total VA, general trend variable	14 countries (Europe, US and Canada), environmental goods sector, 1980-2000	**insign** for dummies and index variable, **positive** for SO2 emission level
Johnstone, Hasic and Popp (2010)	Renewable energy patents by technological area	Dummy of public R&D, tax measures, investment incentives, differentiated tariffs, voluntary programs, quantity obligations, tradable certificates, policy clusters, composite policy variable (contemporaneous to 4-years lags)	Specific R&D expenditures, electricity consumption,electricity price,total EPO filings	25 OECD countries, renewable energy sector, 1978-2003	**policy specific**

Tab. 2: Selected survivorship studies of the PH

Study	**Competitiveness indicator**	**Environmental regulation proxy**	**Other controls**	**Sample and level of aggregation**	**Estimated regulation effect**
Biørn, 1998	Conditional exit probability	Dummy variable for facilities under annual emission quantities and/or maximum concentrations regulations	Size of petroleum outlets, size of petroleum retail firms that own those outlets, tank ages	Norwegian pulp and paper, iron, steel and ferroalloys and chemical sectors, firm-level, 1976-1991	**negative for pulp and paper, iron, steel and ferroalloys sectors**
Yin et al., 2007	Conditional exit probability	Time variable of Underground Storage Tank regulation introduction, regulatory variable*petroleum outlet size, regulatory variable*tank age, regulatory variable*tank capacity	Size of petroleum outlets, size of petroleum retail firms that own those outlets, tank ages	Michigan petroleum retail market, firm-level, 1992000	**negative for small business**
Greenstone et al., 2012	Conditional exit probability	Country-level dummy variables of ozone, total suspended particulates, sulfur dioxide, carbon monoxide regulations	Census-geographic-division-by-year or Census-geographic-division-by-ASM-panel fixed effects, plant fixed effects	U.S. manufacturing, plant-level, 1972-1993	**positive for ozone regulation, negative for CO2 regulation, insignificant for TSP and SO2 regulation**

Tab. 3: Selected financial studies of the PH

Study	Competitiveness indicator	Environmental regulation proxy	Other controls	Sample and level of aggregation	Estimated regulation effect
Russo and Fouts, 1997	Return on assets	Environmental ratings	4-biggest firm concentration ratio, firm growth rate, firm size, capital intensity, advertising intensity, industry growth rate	firm-level, 1992-1993, cross-section analysis	**negative**
Rassier and Earnhart, 2009	Tobin q	Permitted limits for wastewater discharges	3-years sales growth, capital intensity, assets age, firm size, current ratio, R&D intensity, market share, concentration of the industry in which the firm operates, average size of the facilities owned by a firm, year dummy	the U.S. chemical sector, firm-level, 1995-2000	**negative**
Rennings and Rammer, 2011	Price cost margin (categorial variable)	Dummies of environmental regulation by environmental domains	Herfindahl index, stock of patents and past R&D expenditure over sales, export activity, age, size, capital-labour ratio, dummy of foreign-owned firm, innovation success variables	German manufacturing, firm-level, 2003, cross-section analysis	**policy specific**

Tab. 4: Selected productivity studies of the PH

Study	**Competitiveness indicator**	**Environmental regulation proxy**	**Other controls**	**Sample and level of aggregation**	**Estimated regulation effect**
Gray and Shadbegian, 1993	TFP/LP levels, TFP growth	(Change of) PACE current expenditures share in total shipment , count of environmental inspections, fraction of times a plant is in compliance, emission level	Capital vintage	3 US manuf. sectors, plant-level, 1979-1985	**negative** for PACE current exp., **insign** for other policy proxies
Gray and Shadbegian, 2001	TFP level, Output	PACE current expenditures share in total shipment, PACE*technology dummy, PACE*vintage dummy	Labor, materials and energy expenditures in real terms, real capital stock, time-invariant technology and vintage dummies	US paper and pulp industry, plant-level, 1979-1990	**negative**
Berman and Bui, 2001	TFP growth	Count of active regulations	State dummy, year dummy	US petroleum refining industries, plant-level, 1987-1995	**positive**
Lanoie, Patry and Lajeunesse, 2008	TFP growth	PACE capital expenditures share in total cost - Contemp.,1-2Y lagged, 3Y moving average	Change in level of output, capacity utilisation index, polluting sector and exposed to competition sector dummies, stringency of occupational safety and health regulation	Quebec manufacturing sectors, sector-level data 1985-1994	**negative** short-term effect, **positive** long-term effect for less polluting industries
Greenstone et al., 2012	TFP level	Country-level dummy variables of ozone, total suspended particulates, sulfur dioxide, carbon monoxide regulations	Census-geographic-division-by-year or Census-geographic-division-by-ASM-panel fixed effects, plant fixed effects	U.S. manufacturing, plant-level, 1972-1993	**negative** effect of ozone regulation **positive** effect of carbon monoxide regulation on refineries productivity
Marin and Lotti., 2014	TFP level	Induced patents		Italian manufacturing firms, 1995-2006	**positive**

Tab. 5: Selected international trade studies of the PH

Study	**Competitiveness indicator**	**Environmental regulation proxy**	**Other controls**	**Sample and level of aggregation**	**Estimated regulation effect**
Tobey, 1990	Multilateral export flows	Time invariant self-reported env.regulation strictness measure for exporting and importing countries against the US as benchmark country		23 developed and developing countries, cross-section for year 1975	**insign**
Van Beers and Van den Bergh et al., 2000	Bilateral export flow: aggregate and for pollution intensive sectors	Self-reported environmental regulation measure of a country's perceived stringency obtained from the questionnaire (time-invariant)	Exporting and importing country GDP, population, geographic distances, land area, dummy of participation in EC and EFTA, % R&D expenditures, FDI as %GDP, World bank index of rule of law	23 developed and developing countries, sector-level data cross-section 1975	**positive** for paper industry, **insign** for chemicals and steel, **negative** for mining and non-ferrous metals
Costantini and Crespi, 2007	Bilateral export flow related to env.-friendly technologies in energy sector	Public and private current PACE as %GDP, public investments on environmental protection as %GDP, energy and env.tax revenue/total revenues, Kyoto Protocol, CO2 emissions %GDP	GDP, population, geographic distances, number of patents in energy sector, the number of total patents from residents, % of R&D expenditures, technological capability index for importing countries, FDI as %GDP, World bank index of rule of law	OECD countries, technologies for energy sector, 1996 - 2005	**positive**
Costantini and Mazzanti, 2011	Bilateral export flow	1-year lagged PACE as a % GDP, energy and environmental tax as % total revenues, EMAS	1-2 years lagged net export, geograph. border, extensive and intensive trade margins, similarity index, knowledge stock for exp. countries, tech. capability index for imp. countries, country-pair size, relative endown., firms heterogeneity, temp. shocks and geograph. dummies	EU15 countries, 5 macro-sectors,1996-2007	**positive** effect of environmental tax in high-tech sector, **sector and policy specific**

Tab. 6: Selected combined studies of the PH

Study	Competitiveness indicator	Environmental regulation proxy	Other controls	Sample and level of aggregation	Estimated regulation effect
Rave and Rammer, 2011	Indicators of product innovations novelty, ability to achieve unit cost reductions for process innovations, firm profitability	Dummies of environmental regulation by environmental domains	Firm size, R&D activity, share of graduated employees, location, co-operation in innovation activities	German manufacturing, firm-level, 2003	**policy and innovation specific**
Hamamoto, 2006	R&D expenditures	1-year lagged PACE	Government R&D subsidy, VA	Japanese manuf. sector-level, 1966-1976	**positive innov. effect**
	TFP growth	Regulation induced incremental R&D	Non-regulation induced incremental R&D, change in average age of capital stock		**positive productivity effect**
Yan, 2012	R&D expenditures	1-year lagged PACE		Taiwan manuf. sector-level,	**positive innov. effect**
	TFP growth	Regulation induced incremental R&D	Non-regulation induced incremental R&D, change in average age of capital stock		**positive productivity effect**

Tab. 7: Regulation variables in the literature

Variables	Relevant papers	Drawbacks and endogeneity issues
PACE, PACE/VA, PACE/GDP, PACE/Total Cost, PACE/Shipments	Jaffe and Palmer, 1997; Brunnermeier and Cohen,1998; Gray and Shadbegian,1993, 2001; Costantini and Mazzanti, 2011	Depend on the nature of an industry's response to regulation (due to organisational efficiency, innovativeness), energy-intensity of the industry, simultaneity problem: possibly better performing industries are more regulated, don't consider possible subsidies for the enterprises burdened by the regulation-induced production costs increase, self-reported measures, could suffer from the measurement errors.
Emission/Energy use level, Emission/Energy Intensity	De Vries and Withagen, 2005; Constantini and Crespi, 2008	Ambiguous interpretation, depends on economic performance and structural change of industry/country, oil prices, milder weather, economic conditions etc.
Count of active regulations	Gray and Shadbegian,1993; Berman and Bui, 1999; Costantini and Mazzanti, 2011	.No information about policy stringency
Policy adoption dummies	Johnstone et al, 2008	No information about policy stringency, could lead to multicolinearity problems
Self-reported indicators	Tobey, 1990, 1993	
Composite indicators of environmental regulation	Johnston, 2010; Vona and Nicolli, 2012	
Share of environmental tax revenue in total government revenue	Constantini and Crespi, 2008, Costantini and Mazzanti, 2011	Depend on energy-intensity of industry, simultaneity problem: possibly better performing industries are more regulated, don't consider possible subsidies for the enterprises burdened by the regulation-induced production costs increase
Green patents	Rennings and Rammer, 2011, Martin and Lotti, 2014	

Environmental regulation and competitiveness: empirical evidence from European manufacturing sectors

Abstract

This paper represents an empirical investigation of the eaknd trongorter Hypothesis (PH) focusing on the manufacturing sectors of European countries between 1997 and 2009. By and large, the literature has analyzed the impact of environmental regulation on innovation and on productivity generally in separate analyses and mostly focusing on the USA. The few existing studies focusing on Europe investigate the effect of environmental regulation either on green innovation or on performance indicators such as exports. We instead look at overall innovation and productivity impact that are the most relevant indicators for the trongH. This approach allows us to account for potential opportunity costs of induced innovations. As a proxy of environmental policy stringency we use pollution abatement and control expenditures (PACE), which represent one of the few indicators available at the sectoral level. We remedy upon its main drawback, that of potential endogeneity of PACE, by adopting an instrumental variable estimation approach. We find evidence of a positive impact of environmental regulation on the output of innovation activity, as proxied by patents, thus providing support in favor of the eakH in line with most of the literature. On the other front, we find no evidence in favor or against the trongH, as productivity appears to be unaffected by the degree of pollution control and abatement efforts.

1 Introduction

In this paper we investigate the impact of environmental regulation on the economic performance of the European manufacturing sectors. The standard neoclassical view holds that (strict) environmental regulation adversely affects productivity and competitiveness by imposing constraints on industry behavior. On one hand, firms face direct costs such as end-of-pipe equipment or the R&D investment necessary to modify production activities. On the other hand, firms' budgets are limited due to financial constraints. By committing resources to comply with regulation, firms also bear indirect costs because they cannot invest in other more profitable endeavors related, for example, to their core business (see Gray and Shadbegian, 1993).

Porter (1991) and Porter and Van der Linde (1995) challenged this view by arguing that well-established environmental policy would benefit both the environment and the firm. Well-crafted and well-enforced regulation would push the firm to pursue otherwise neglected investment opportunities, resulting in a "win-win" situation of better environmental quality and higher firms' productivity.

Such an outcome, which has been referred to as Porter Hyposesis (PH), arises because firms face market imperfections, such as imperfect information, organisational inertia or control problems. In Porter's view, environmental regulation would push firms to overcome some of these market failures by promoting innovation aimed at lowering the cost of compliance. Regulation-induced innovation would in turn result in increased resource efficiency, higher product value and enhanced firms' productivity. As a result, compliance costs could be offset and firms would have a competitive advantage with respect to, for example, firms in foreign countries not subject to similar regulation.

Initially formulated in rather general terms, the PH can be declined as three possible and distinct research statements (Jaffe and Palmer, 1997). First, the *"narrow"* version of the PH postulates that flexible environmental regulation, such as market-based instruments, increases firms' incentives to innovate compared to prescriptive regulation, such as performance-based or technology-based standards. Second, the *"weak"* version of the PH postulates the positive effect of well-crafted environmental regulations on environmental innovations (even when environmental innovation comes at an opportunity cost that exceeds its benefits for a firm). Finally, the *"strong"* PH states that innovation induced by well-crafted environmental regulation could more than offset additional regulatory costs, and, consequently, increase firm' s competitiveness and productivity.

Since the early 1990s proving or disproving the PH with empirical evidence has been the focus of much literature (see Rubashkina, 2013 for a review). Most of the studies, however, focus on the US, while the empirical evidence for Europe is scant. This is particularly troublesome given the recent European policy developments. Since the end of 1980s the European environmental policy became more stringent. An initial commitment to the strategic reorientation of environmental policies in the EU gradually took place since 1987 , with the introduction of the 4th Environment Action Programme (EAP) (Hey, 2006). Since then, Europe increasingly moved away from command-and-control regulation towards the implementation of new market-based instruments. In particular, an unprecedented regulatory boom took place starting in 1996. Among the first and most relevant policy interventions are the IPPC-Directive (1996/61), the Ambient Air Quality Directive (96/62), the Water Framework Directive (2000/60) and the NEC-Directive (2001/81). They were followed by EU Emission Trading Scheme (2003/87/EC).

Today, European countries are committed to both the "Lisbon Agenda", which stresses increased competitiveness, economic growth and job creation, and to the "Gothenburg Agenda", which focuses on sustainable development. Integration of environmental protection into other EU policies is seen as a necessary step. The European Commission argues that environmental policies and increased competitiveness are not mutually exclusive, but can indeed strengthen one another (European Commission, 2010). Moreover, in light of the economic crisis, the concept of "green recovery" (Edenhofer and Stern, 2009) gained the center-stage.

This policy discourse is in line with the claims underlying the PH, as environmental regulation can in fact result in enhanced competitiveness. However, this link has not been proven and many worry that environmental regulation will place an excessive burden on European industries, thereby stifling growth and damaging their competitiveness in an increasingly global market place. Testing the link between environmental regulation and competitiveness indicators is thus particularly relevant for Europe, where country-specific dynamics is likely to play a big role within the EU. While environmental policy initiatives are generally drafted at the European level, their implementation still lies with the national governments, leading to big countries disparities with respect to the stringency and implementation of such policies.

The goal of this paper is to extend the analysis of the PH using cross-country sector-level data for European countries. We investigate the "strong" PH and assess whether environmental regulation enhances or stifles sectoral innovation and productivity.

We contribute to the literature in several ways. First, unlike the few previous contributions focusing on Europe (De Vries and Withagen, 2005, Johnstone, Hascic and Popp, 2010, Constantini and Crespi, 2008), we look at overall competitiveness and innovation, that are the most relevant indicators for the "strong" PH. Previous studies mostly focused on the "weak" PH and investigated the effect of environmental regulation on energy efficiency and renewable energy innovation and performance. While generally concluding that environmental innovation positively responds to environmental policy, these studies do not consider the opportunity costs of environmental innovation, and cannot consider the overall performance of different EU manufacturing sectors.

Second, we bring together all the recent available data for the EU countries and investigate the PH at the sectoral level. With respect to a country-level analysis we can thus better capture the effects of sector-specific environmental policies, on the one hand, and the dynamics of competition that takes place within a sector, on the other hand. To our knowledge, this is the first empirical analysis investigating the effect of environmental regulation on overall innovation and productivity at the sectoral level in the EU.

Third, we provide a first combined assessment of both innovation and competitiveness impact of environmental regulation in the context of the PH using the European data. Previous contributions focused either on assessing the impact of regulation on environmental innovation (De Vries and Withagen, 2005, Johnstone, Hascic and Popp, 2010) or on competitiveness (Constantini and Crespi, 2008, Mazzanti and Constantini, 2011), but no empirical analysis focusing on Europe addresses both questions.

Finally, we use pollution abatement and control expenditures (PACE) at the sectoral level as an environmental policy indicator, which has not been previously employed in the investigation of the PH in Europe. PACE measure the consequence of government environmental policies and regulations and include the flow of investment and current expenditure directly aimed at pollution abatement and control. We address potential endogeneity of PACE employing an instrumental variable approach. With the exception of a few papers (De Vries and Withagen, 2005, Carrion-Flores and Innes, 2010, Kneller and Manderson, 2012) the existing literature generally does not explicitly account for the endogeneity problem of environmental policy variables in the PH context, whereas it might lead to biased estimates of environmental regulation effect on economic performance.[1]

The paper proceeds as follows. Section 2 briefly summarizes the literature on the PH. Section 3 describes the competitiveness indicators used in our empirical application while Section 4 presents the environmental regulation proxies. Section 5 presents descriptive statistics while the empirical results on the link between environmental policy and innovation and competitiveness are presented in Sections 6 and 7, respectively. Section 8 provides robustness checks and Section 9 concludes and discusses further research avenues.

2 Empirical Framework and Literature Review

The general framework guiding the empirical investigation of the PH in the literature can be represented as follows:

$$C = f(ER, Z) \tag{1}$$

[1] Also in the other large literature on pollution heaven hypothesis that investigates the impact of environmental regulation on manufacturing enterprises relocation only a few papers account for endogeneity of environmental policy variables (Xing and Kolstad (2002), Ederington and Minier (2003) and Levinson and Taylor (2003)).

where C is a competitiveness indicator, ER is an environmental regulation stringency variable and Z are other control variables.

The empirical literature investigating the link between environmental regulation and competitiveness in the context of the PH is vast, but mostly focused on the US. With respect to testing the innovation impact, Jaffe and Palmer (1997) studied how environmental regulation stringency, proxied by PACE, affects overall innovation in US manufacturing sectors, proxied by either sector-level R&D expenditures or USPTO patents applications. Their results point to a significant positive link between regulation and R&D expenditures, whereas patents are not affected by more stringent regulation.

Several subsequent studies addressed similar questions, mostly focusing on the "weak" PH. Using plant- or sector-level US data they investigated the link between PACE and environmental patents (see, for example, Lanjouw and Mody, 1995, Brunnermeier and Cohen, 2003), generally concluding in favor of Porter's idea that environmental regulation spurs environmental innovation.

Conversely, the results of early studies on the "strong" PH in the US, such as Gray and Shadbegian (1993, 2001), concluded that environmental regulation caused a productivity slowdown. The authors attributed this to a displacement of "productive" investment by environmental regulation. However, these studies investigated the impact of early command-and-control policies in the US and not of market-based environmental policy, as implied by the PH in its original form.

The sector-level analytical framework has been also applied to a handful of other countries. Hamamoto (2006) investigated both innovation and productivity responses to environmental regulation, proxied by PACE, in Japan. A similar framework and environmental regulation proxy was used by Yang, Tseng and Chen (2012) for Taiwan, whereas Lanoie, Patry and Lajeunesse (2008) focus on productivity effects of environmental regulation in Canada. These contributions support the previous conclusions on the positive effect of environmental regulation, captured by PACE, on innovation and provide some evidence of a positive impact of productivity.

Only a few studies test the effect of stringent environmental regulation on competitiveness in Europe. De Vries and Withagen (2005) focus on SO_2 reduction-related innovation and test the "weak" PH at the country-level on a sample of twelve European countries plus US and Canada. They use a number of environmental regulation proxies, such as dummies indicating the adoption of international environmental protocols, an index of Environmental Sensitivity Performance and SO_2 emission levels. Johnstone, Hascic and Popp (2010) focused on the "weak" PH in the renewable energy sector in twenty-five OECD countries and investigated the relation between environmental regulation and patents using various environmental policy adoption dummies. Constantini and Crespi (2008) investigated the "strong" PH in the energy sector of seventeen European countries plus Japan, Canada and US. They focused on export effects and employed several environmental policy indicators such as PACE, the share of environmental tax in total government revenue, CO_2 emissions intensities and a ratification dummy of the Kyoto Protocol. Finally, Mazzanti and Constantini (2011) extended the investigation of the environmental regualtion-export nexus to a broad range of manufacturing sectors in the EU-15 using PACE and environmental tax share as policy variables.

There are a few limitations shared by the EU-based studies just mentioned, that are worth noting. First, most of them, with the exception of Mazzanti and Constantini (2011), are country-level analyses. As a result, they cannot account for heterogeneity in the sectors' responses to the regulation. Mazzanti and Constantini (2011) do have a sectoral dimension, but the environmental regulation variables employed are country-specific and do not exhibit sectoral variation.

Second, most studies testing the "weak" PH in Europe focus on how environmental innovation (such as renewable energy or energy saving patents) responds to regulation. They therefore do not test the effect of stringent environmental regulation on total manufacturing innovation and performance. Looking only at environmental innovation is misleading, because the opportunity costs of environmental innovation are not accounted for. In fact, environmental regulation could cause an increase of environmental innovation, while (more valuable) innovation in other fields is not pursued due to budget constraints. Therefore, looking at environmental innovation only is a partial way to test the PH.

Third, European studies that focus on the "strong" PH mostly focus on export effects and do not test how productivity responds to stringent environmental policy. And this is however the most controversial statement of the PH.

3 Competitiveness indicators

To test the validity of PH in European manufacturing sectors we use innovation and productivity indicators as proxies of competitiveness. We describe each of them in detail below, while we present the proxies for environmental policy stringency in the next section.

3.1 Innovation proxies

To test the innovation impact of environmental regulation, we use both R&D expenditures and patent statistics as measures of innovation activity. Both these proxies have been widely used in the literature (Griliches, 1990). Industrial R&D expenditures represent an input of the innovation production function, and measure the effort of private firms in pursuing innovation. Industrial R&D expenditures expressed in millions of euro at 2005 prices are taken from the OECD ANBERD database (OECD, 2012a). We complement this source with data from EUROSTAT (EUROSTAT, 2012a) for some missing countries like Bulgaria, Sweden, Slovakia and the UK.[2] The data are available for fifteen countries over the period 1996-2009. [3]

Conversely, patent statistics approximate the output of the knowledge production function (see, for example, Joutz and Gardner, 1996, Johnstone et al., 2010). To a certain extent, patent applications proxy for the productivity of R&D at the sectoral level. Patent indicators suffer the major drawback of greatly differing in quality and in the magnitude of inventive output (Griliches, 1990). For this reason, we extract data on patents applications by inventors to the EPO. EPO application data are superior to data from national patent offices, since the difference in costs between a national application and an EPO application provides a quality threshold which eliminates low-value inventions (OECD, 2009).

Patents statistics are extracted from the EUROSTAT Patent statistics database (EUROSTAT, 2012b).[4] Patent applications are assigned to a country according to the inventor place of residence, using fractional counting if there are multiple inventors. Data on sectoral patent applications are available for all EU countries for the period 1977-2009.

3.2 Productivity proxies

To test the productivity impact of environmental regulation, we use both Total Factor Productivity (TFP) and Labor productivity (LP), which measure two distinct aspects of sectoral productivity. TFP shows the time profile of how productively combined inputs are used to generate gross output. Conceptually, TFP captures technical change. In practice, it reflects also efficiency change, economies of scale, variations in capacity utilisation and measurement errors (OECD, 2001). Conversely, LP shows the time profile of how productively labour is used to generate value added. Labour productivity changes reflect the joint influence of changes in capital, as well as technical, organisational and efficiency change within and between firms, the influence of economies of scale, varying degrees of capacity utilisation and measurement errors. Following Inklaar and Timmer (2008), we compute a Value Added-based LP measure, and a Gross Output-based TFP.

[2] The R&D data from EUROSTAT are originally reported in current Euro, so we deflate them with the 2005 GDP deflator.

[3] A concern related to cross-country comparability of the R&D data from the OECD ANBERD must be noted. R&D expenditures are classified by industry according to two different types of criteria: by main activity or by product field. For some countries R&D expenditures are calculated by main activity, allocating all R&D expenditures according to the principal activity of a firm (though large firms could have important R&D activities in secondary activities). On the contrary, for other countries, R&D data are calculated by product field, disaggregating the R&D expenditures of diversified firms into different activities. Notwithstanding these differences, we use R&D proxy to provide comparable results with previous literature.

[4] EUROSTAT patent data is based on the EPO Worldwide Statistical Patent Database (PATSTAT). The data excludes applications to national patent offices of the Member States and Patent Cooperation Treaty (PCT) applications made to the EPO that are still in the international phase.

5

For both productivity measures we use data from the EU KLEMS database (EU KLEMS, 2009) and the WIOD Socio-Economic Accounts database (WIOD, 2012). The EU KLEMS database provides Gross Output, Value Added, inputs indicators for capital, labor and intermediate inputs to construct TFP and LP measures. The EU KLEMS database has the advantage of providing capital and labor inputs both in absolute and in constant-quality indices terms. The latter are obtained by weighting the components of each input by their marginal product and allow to account for the wide differences in the productivity of various types of labour and assets over time. Using these input indices a quality-adjusted TFP estimate that proxies for the disembodied technological progress can be computed. However, the EU KLEMS allows to construct the quality-adjusted TFP only in growth terms (due to the specific features of adjusted input indices). Moreover, due to bad coverage of capital stock data we were able to construct the productivity indicators in absolute terms only for eleven EU countries such as Czech Republic, Finland, Hungary, Lithuania, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden and the United Kingdom over the period 1997-2007. The productivity indicators in constant-quality terms are available only for eight countries as the relevant data for Lithuania, Poland and Portugal are missing.

Following the previous literature on the "strong" PH (Gray and Shadbegian, 1993, 2001; Lanoie, Patry and Lajeunesse, 2008, Hamamoto, 2006), we estimate productivity equations both in levels and in growth rates, as there is no a priori guide to the use of levels or growth rates. Given our data constraints, and in particular the availability of quality-adjusted indexes only in growth rates terms, we use two different TFP measures in our empirical investigation. One is a"raw" TFP indicator that is not adjusted for the inputs' quality composition (available both in levels and growth for eleven countries of the sample) and another is the quality-adjusted TFP growth indicator (available for eight countries of the sample).

4 Environmental Policy Indicator

To proxy for environmental regulation we use Pollution abatement and control expenditures (PACE) as a policy indicator. There has recently been a surge of interest in measures of environmental policy stringency. A few alternatives have been proposed (Brunel and Levinson, 2013; Botta and Kozluk, 2014; Nesta, Vona, and Nicolli, 2014): none of them is ideal, as each indicator has got pros and cons both from a conceptual and a practical perspective (Brunel and Levinson, 2013). The PACE indicator has not been previously used in the context of sector-level studies of the PH in Europe and is

[5] We provide the details on the construction of TFP and LP in Appendix A. Here, we only point to some major issues linked with the computation of TFP which affect our empirical choices.

particularly well suited because, unlike other indicators (Nesta, Vona, and Nicolli, 2014), it provides information on sector-specific responses to environmental policy.

PACE are purposeful activities aimed directly at the prevention, reduction and elimination of pollution or nuisances arising as a residual of production processes or the consumption of goods and services (OECD, 1996). PACE arise as the consequence of government environmental policies and regulations and include the flow of investment and current expenditure directly aimed at pollution abatement and control. PACE data for the EU manufacturing sectors are available for the period 1997-2009.

To collect the data on these regulation variables we rely on two sources. When possible we use data on nvironmental protection expendituresrom EUROSTAT (EUROSTAT, 2012c). We then fill missing observations with comparable data from various National Statistics Offices (of Cyprus, Estonia, Lithuania, Slovenia, Spain, Sweden and United Kingdom). PACE is reported in million Euros. We use the sector-specific Producer Price Index (PPI) to convert PACE nominal values into constant prices figures. There are number of countries that do not report PACE data by sectors, namely Denmark, Ireland, Luxembourg, Malta and Italy. Moreover, data for Austria, Belgium, France, Germany, Greece, and Latvia contain very few observations. We therefore exclude these countries from the analysis. Thus, the PACE data we are going to use in our analysis refer to seventeen European countries. It should be noted that also for these countries the data have a number of time series gaps.

5 Descriptive Statistics

The period of analysis and the country sample have been selected on the basis of the data availability of environmental regulation indicators. Our sample is an unbalanced sector-level panel dataset covering 17 European countries: Bulgaria, Cyprus, Czech Republic, Estonia, Finland, Hungary, Lithuania, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom for the years 1997-2009. [6]

The level of aggregation by industrial sectors varies across the five different data sources we use to collect our variables (EUROSTAT, EU KLEMS, WIOD, OECD STAN and OECD ANBERD). We base our analysis on the sectoral classification of the PACE variable, which includes nine macro sectors. The classification and the reference to the the two-digit European NACE revision 1.1 sectoral classification is shown in Table 1. Table 2 provides summary statistics of the main variables in the overall sample, while Table 3 provides statistics by country.[7]

[6] We exclude the other EU countries as they do not provide the required data on environmental regulation.

[7] We detected 24 outliers with unreasonably high PACE/VA ratio (several observations for Cyprus, Estonia and Slovenia) and patent/VA ratio (several observations for Slovenia). These observations were excluded from the sample.

Tab. 1: Classification of Industrial Sectors

#	Sector	NACE Rev.1.1
1	Food products, beverages and tobacco	15-16
2	Textiles and textile products; leather and leather products	17-19
3	Wood and wood products	20
4	Pulp, paper and paper products; publishing and printing	21-22
5	Coke, refined petroleum products and nuclear fuel	23
6	Chemicals; rubber and plastic products	24-25
7	Other non-metallic mineral products	26
8	Basic metals	27
9	Fabricated metal, Machinery and equipment, electrical and optical equipment, transport equipment, manufacturing n.e.c.	28-36

Source: International Standard Industrial Classification of all economic activities.

Tab. 2: Summary statistics (1997-2009)

Variable		Unit	Mean	Std. Dev.	Min.	Max.
R&D	Total R&D expenditures	Mln.constant euro	301.05	1113.81	0.00	9389.98
PAT	Total patents application to EPO	N patent application	100.24	393.37	0.00	3570.72
TFP	Total Factor Productivity (based on GO)		1.19	0.44	-0.39	2.06
TFP growth	Total Factor Productivity growth (based on GO)		0.01	0.04	-0.55	0.30
PACE	PACE	Mln.constant euro	91.34	176.03	0.00	1663.95
VA	Value Added	Mln.constant euro	4314.60	10933.69	0.00	112414.7
PATstock	Patent stock	N patent application	782.43	3131.01	0.00	29187.14
R&Dstock	R&D stock	Mln.constant euro	2307.59	7764.29	0.00	66205.59
GOVR&D	Share of government R&D in total government exp.	%	1.27	0.45	0.36	2.08
Export	Export intensity	%	0.63	1.19	0.05	15.69
Import	Import intensity	%	0.33	0.18	0.04	0.97
Death	Death rate	%	0.13	0.33	0.00	6.28
Birth	Birth rate	%	0.12	0.23	0.00	2.76
EI	Energy intensity	TOE per bln.constant euro	1.15	2.48	0.02	42.41

Source: own computations based on the EUROSTAT, the EU KLEM, the OECD STAN, the OECD ANBERD and the WIOD.

Tab. 3: Summary statistics of the main variables by countries (1997-2009)

Country	PACE/VA	R&D/VA	PAT/VA	TFP	TFP growth
Bulgaria	5.28	-	5.13	-	-
Cyprus	3.00	-	11.40	-	-
Czech Republic	4.37	1.87	6.89	1.02	0.02
Estonia	3.28	2.16	12.88	-	-
Finland	2.79	4.85	25.49	1.27	0.02
Hungary	3.68	1.50	7.79	1.02	0.00
Lithuania	3.46	-	4.90	1.01	0.02
Netherlands	4.38	4.02	38.86	1.17	0.01
Norway	2.81	4.36	16.95	-	-
Poland	3.78	0.42	2.21	1.03	-0.01
Portugal	2.88	1.19	4.01	0.98	-0.00
Romania	5.85	3.12	1.83	-	-
Slovakia	3.62	2.06	4.11	-	-
Slovenia	3.59	2.47	12.07	1.32	0.01
Spain	2.01	2.22	6.73	1.09	0.01
Sweden	5.14	-	30.84	1.23	0.01
United Kingdom	2.54	5.49	15.03	1.55	0.02
Total	3.63	2.86	12.73	1.19	0.01

Source: own computations based on the EUROSTAT, the EU KLEM, the OECD STAN, the OECD ANBERD and the WIOD.

With regards to the competitiveness indicators, there are striking difference between new and old Member States. In particular, Austria, Belgium, Denmark, Finland, Netherlands, Norway, Sweden and the UK have patent and R&D intensities which exceed several time those of other countries. The level of TFP is highest in Finland, Slovenia, Sweden and the UK. TFP growth is highest in the Czech Republic, Finland, Lithuania and the UK, whereas it is negative in Poland and Portugal. Concerning environmental expenditures an average share of PACE in the final sample makes 3.6 percent in Value Added and 0.9 percent in Gross Output. Finland, Portugal, Norway, Spain and the UK are behind the other countries in terms of share of environmental expenditures in VA (that ranges between 2-3 percent). We can also observe larger environmental expenditures in new Member States than in old Member States over the sample period, as the former needed to catch up with European legislative requirements in a relatively short period of time (in new Member States PACE/VA ranges between 4-6 percent). Among the old Member States Sweden and the Netherlands have the highest expenditures for compliance with environmental regulation (PACE/VA ranges between 4-5 percent).

Table 4 provides descriptive statistics by sector. Some sectors, such as sector 5 “Coke, refined petroleum products and nuclear fuel”, 6 “Chemicals; rubber and plastic products” and 9 “Machinery and equipment”, have patent and R&D intensities which are twice the average. Their patent intensity ranges (19-36 patents per billion of euro against an

Tab. 4: Summary statistics of the main variables by sectors (1997-2009)

Sector	PACE/VA	R&D/VA	PAT/VA	TFP	TFP growth
1	2.60	1.05	4.15	1.06	0.01
2	1.52	1.25	4.56	1.12	0.01
3	2.38	0.48	0.90	1.21	0.01
4	3.25	0.60	2.17	1.31	0.01
5	9.49	4.88	19.17	0.29	0.01
6	4.03	8.17	36.97	1.44	0.01
7	3.45	0.99	7.42	1.67	0.02
8	6.08	1.90	11.93	1.40	0.01
9	1.16	5.99	29.10	1.04	0.01
Total	3.63	2.86	12.73	1.19	0.01

Source: own computations based on the EUROSTAT, the EU KLEM, the OECD STAN, the OECD ANBERD and the WIOD.

average value of 13 patents per billion of euro and 4.9-8.2 percent R&D intensity versus an average value of 2.9 percent). The highest TFP in terms of level is observed in sectors 6 "Chemicals; rubber and plastic products", 7 "Other non-metallic mineral products" and 8 "Basic metals". With regards to PACE, we observe sizeable differences between the sectors 5 "Coke, refined petroleum products and nuclear fuel", 6 "Chemicals; rubber and plastic products" and 8 "Basic metals" that spend more on pollution abatement and control activities than an average European sector (their shares of PACE in VA are 9.5 percent, 4.0 percent and 6,1 percent, respectively, against an average share of 3.6 percent).

6 Environmental regulation and innovation activity

We begin our empirical analysis by testing the relations between environmental regulation and innovative activity, while empirical analysis the impact of environmental regulation on productivity is presented in section 7.

6.1 Empirical strategy

Our starting point is an equation similar the one used in the paper of Jaffe and Palmer (1997) extended for multi-country sector-level analysis. The log-log specification relating innovation to environmental policy proxies reads as follows:

$$\ln INNO_{ijt} = \beta_1 \ln ER_{ijt-q} + \gamma \ln \mathbf{X}_{ijt-1} + \alpha_{ij} + \mu_t + \epsilon_{ijt} \tag{2}$$

Where $INNO_{ijt}$ is either total R&D expenditures (R&D) or total patent applications (PAT) in country i sector j and time t. Environmental regulation (ER) is PACE [8]. Equation (2) controls for both unobserved and observed sector-country specific heterogeneity. The main difference between the regressions with the R&D and the PAT indicators lie in the lag structure considered in the estimation for ER, as discussed in detail below. Due to the data availability R&D and patent equations are estimated for the period 1998-2009 and 1997-2009, respectively.

To deal with factors that could affect a sectoral innovation performance we include the vector of sector- and national-level covariates ($\mathbf{X}$). Sector-level covariates include Value Added (VA), knowledge stock (INNOstock), import penetration (Import), export intensity (Export), enterprises birth rate (Birth) and death rate (Death). Country-level covariates include public support to private R&D (GOVR&D).

We account for the impact of public support to private R&D using the share of R&D appropriations in total government expenditures. The data comes from the GBAORD OECD database (OECD, 2012a) but has the disadvantage of being reported only at the aggregate country level with no sectoral detail.

Among the determinants of innovation, a prominent role is played by technology-push factors, as argued by Schumpeter (1943). Thus, on the supply side we add a knowledge stock variable (INNOstock) capturing previous innovation experience, which has a positive influence on the innovation capacity of a given country because innovators can "stand on the shoulders of the giants" (Caballero and Jaffe, 1993). Firms/industries which exhibit greater past investment in technological development are also more likely

[8] Alternatively, we can regress a percentage share of R&D in VA or a share of PAT in VA on a PACE share in VA. However, a measurement error in value added could cause equation 2 to exhibit spurious correlation. Thus, we estimate the equation in ratio form as a Robustness check in section 7.4. The results on PACE are very similar to those reported here.

to engage in innovative practices in the future (Baumol, 2002). The stock is calculated using the perpetual inventory method (Verdolini and Galeotti, 2011) as follows:

$$INNOstock_{ijt} = INNO_{ijt} + (1-\delta)INNOstock_{ijt-1} \tag{3}$$

where δ is the decay rate, set at a value of 0.1 as suggested by Keller (2002) and the initial innovation stock is calculated as follows:

$$INNOstock_{ijt_0} = \frac{INNO_{ijt_0}}{(\delta + \bar{g}_{ij})} \tag{4}$$

In equation (4) we use t_0 is the initial year of stock calculation and $\bar{g}_{ij}$ is the sector-country specific average innovation growth of the three years preceding t_0. In the case of the R&D equation the knowledge stock is based on private sectoral R&D and $t_0 = 1998$ (as the earlier data are not available). In the patent equation the stock is computed using sectoral patent applications and $t_0 = 1993$.

We include import penetration (Import) as a proxy of external competition. Many studies following Schumpeter (Schumpeter, 1943) postulate a positive influence of market concentration on innovation. Schumpeter argued that market concentration reduces market uncertainty and motivates firms to invest in R&D. Other authors argue the opposite, claiming that concentration leads to inertia and hinders innovation due to lacking competitive pressure (Levin et al.,1985). Therefore, the sign associated with the effect of external competition on innovation is ambiguous. The import penetration is calculated as the ratio of import over the sum of domestic and import production. The data for sector level import intensities are taken from the WIOD Input output database (WIOD, 2012).

To control for the effect of sector's structural change due to enterprises creations, deaths or relocations on innovation intensity we incorporate enterprises birth (Birth) rate and deaths rates (Death) indicators in the equation. This structural changes might also affect environmental costs intensity. In particular, if enterprises shutdown or relocate due to strict environmental policy, it is likely that PACE intensity decreases as the most burden firms leave the market. The birth rate is defined as number of new enterprises over total enterprises, whereas the death rate is a number of death enterprises over total enterprises.[9] The data are obtained from EUROSTAT Detailed enterprise statistics on manufacturing subsections (EUROSTAT, 2012a).

We supplement the vector of controls with export intensity (Export) which controls

[9] Enterprises created or closed solely as a result of e.g. restructuring, merger or break-up are not included in this data. Due to the original classification of the database "Fabricated metal" is included in sector 8, rather than in sector 9 (EUROSTAT, 2012a).

for a sector's participation in foreign trade. If foreign markets are more responsive to variety changes, an increase in export intensity could lead to more R&D spending (Brunnermeier and Cohen, 2003). Moreover, strong competition abroad can encourage innovation, especially if a regulated firm is competing with firms in countries with less stringent environmental regulations and lower wages (Kneller and Manderson, 2012). Export intensity is calculated as the ratio of exports over domestic production, based on data drawn from the WIOD (2012).[10]

Finally, as larger industries are likely to have greater absolute levels of PACE, and are also more likely to have the resources necessary to meet the fixed costs, and bear the risks, involved with undertaking investments in innovation we include VA as a scaling variable.

The control variables summarised by $\mathbf{X}$ are lagged once to avoid simultaneity problems with innovation activity. Besides production (or VA) to innovation, causality could run in the opposite direction accounting for a possible boost of production scale due to successful innovation. Similarly, two-way causation could exist between innovation and exporting: innovation could positively affect exports through induced competitiveness on international markets. Finally, bidirectional causation could arise between innovation and external competition, as innovation performance of local producers could affect the degree of import penetration.

To test the dynamic effect of environmental regulation on innovation stressed by many authors (for example, Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003; Hamamoto, 2006) we incorporate a lag structure for environmental regulation variables. It is reasonable to assume that firms immediately react to the introduction of regulation, and get involved into R&D. However, we can also assume that in some cases it takes time to mobilize the resources necessary for R&D investments. Therefore, in the equation where R&D is used as a dependent variable, we test both contemporaneous, one and two years lagged effects of the environmental policy due to different assumption about reaction time of firm to environmental regulation. The choice of the number of lags is based on previous findings which show that the policy variable is most significant with lags between zero and two years (for example, see Brunnermeier and Cohen, 2003, Hamamoto, 2006 and Johnstone et al., 2010).

Given the different nature of the R&D and patent data, we assume a different lag structure in R&D and patent equations. Specifically, we assume that the whole innovation process from R&D investment to patent application takes time and that environmental

[10] Due to the original classification of the WIOD database "Fabricated metal" is included in sector 8, rather than in sector 9. We correct values associated with sectors 8 and 9 by applying Value Added share of "Fabricated metal" in aggregated metal sector from the EU KLEMS (March 2008 Release, which reports these two sub-sectors separately). As we could not provide these corrections for countries not reported by EU KLEMS such as Romania, Bulgaria, Cyprus, Lithuania and Estonia export and import data for sectors 8 and 9 for these two countries are missing.

policy-induced innovations could be translated into patents with at least one (or more) year lag period. Thus, we include from one to three years lagged regulation variable in the patent equation. Equation (2) includes country-sector specific effects α_{ij}, which absorb the impact of sector-specific time-invariant characteristics of innovation ability and are also likely to be correlated with PACE and time effects μ_t. [11]

A final issue is the treatment of country-sector effects, whether fixed Effect (FE) or random (RE). The RE model is consistent only if country-sector specific effects are uncorrelated with the covariates, which is unlikely to occur when there are omitted variables. The FE model, instead, is required in the presence of such correlation. However, the FE is less desirable, in that it uses only within variation of the data, that leads to less efficient estimation. The Hausman test allows for discrimination between the two models. Since in our context unobservable factors, that are constant over time but vary across countries and sectors, can affect innovation activity and are also likely to be correlated with the other regressors, we estimate the innovations models using a FE estimator. We validate this choice with the Hausman test: the significance of the statistics associated to the Hausman test confirms that the FE model is to be preferred to the RE model.

It is important to keep in mind that due to data availability issues we carry out estimations of R&D equations on a smaller country sample than the patent equation. In particular, we loose observations on three countries such as Lithuania, Estonia and Cyprus. Therefore, the results of two innovation equations are not directly comparable. [12]

6.2 Estimation results

Tables 5 and 6 report the estimation of R&D and patent effect of environmental regulation, respectively. Columns 1-3 and Columns 4-6 of Table 5 report the results of an immediate and one-year lagged PACE effect on R&D, respectively. Columns 1-3 and Columns 4-6 of Table 6 display the results of one- and two-years lagged PACE effect on patents. As a starting point, in Columns 1 and 4 of both Tables we provide the estimates for the baseline specification similar to Jaffe and Palmer, 1997. The baseline specification is then augmented to control for the knowledge stock, export and import intensity (Columns 2 and 5), and enterprises‘ birth and death rates (Column 3 and 6). The coefficients associated with immediate and one-year lagged impact of environmental

[11] A possible alternative to using country-sector specific fixed effects would be to control for country-specific effects α_i and sector-specific effects α_j separately, but it would be less appropriate in our case. Country-sector specific fixed effects capture the omitted determinants of innovation activity that are likely to affect environment regulation and vary within the same sector across countries. For example, market concentration of local producers could affect cost efficiency, and therefore PACE, as well as determine propensity to R&D. Inclusion of α_{ij} thus allows to correct for omitted-variable bias, assuming these factors do not vary over time.

[12] Results available from the authors upon request show that the findings are robust to use of homogeneous samples.

Tab. 5: R&D effect of environmental regulation: FE estimation

	(1)	(2)	(3)	(4)	(5)	(6)
PACE	0.043	0.006	0.033	-	-	-
	(0.04)	(0.04)	(0.04)			
1Y Lagged PACE	-	-	-	-0.021	-0.055	-0.045
				(0.04)	(0.04)	(0.04)
Lagged VA	0.042	0.070*	0.013	0.084	0.140	0.031
	(0.04)	(0.04)	(0.06)	(0.08)	(0.09)	(0.13)
Lagged GOVR&D	0.043	0.275*	0.311**	-0.076	0.120	0.132
	(0.18)	(0.15)	(0.14)	(0.19)	(0.19)	(0.17)
Lagged R&D stock	-	0.466**	0.654***	-	0.609***	0.633***
		(0.18)	(0.21)		(0.18)	(0.19)
Lagged Export	-	0.433**	0.434*	-	0.404**	0.519***
		(0.18)	(0.22)		(0.15)	(0.18)
Lagged Import	-	-0.095	-0.320	-	-0.472***	-0.633*
		(0.23)	(0.22)		(0.17)	(0.35)
Lagged Death rate	-	-	1.806**	-	-	1.938***
			(0.79)			(0.68)
Lagged Birth rate	-	-	-1.064	-	-	-0.898
			(0.82)			(0.70)
F	1.32*	3.02***	5.61***	1.45**	4.22***	8.46***
Within R-squared	0.05	0.14	0.22	0.05	0.19	0.26
Observations	750	666	515	694	612	512
N.Country-sector	129	112	105	129	111	104

Note: Coefficient estimates from FE. Country-year fixed effects and full set of time dummies included in all models. All the variables are in logs. Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01. The data on Export, Import, Death and Birth are not complete, therefore we loose some obs. when adding these var. in the regressions.

regulation on R&D are insignificant in all the specifications. The results available from the authors upon request show that there is no link between environmental regulation with the lags beyond the two years and R&D. However, judging from the results of Table 6 the one- and two-years lagged patent effect of environmental regulation are positive and significant. Depending on the specification, a 10 percent increase of PACE is associated with a 0,3-0,9 percent increase in number of patent applications. The one-year effect is robust to adding and omitting various controls such as the knowledge stock, export and import intensity, enterprisesirth and death rates. However, the two-years positive effect vanishes when we control for enterprise demographic factors.

Taking together the results of R&D and patent equations, we conclude that environmental regulation has not effect on overall R&D, but increases number of patents in the short- and the medium-run. Therefore, there is no evidence that induced innovations come at opportunity costs for a firm.

The coefficients associated with other controls used in the regressions are in line with expectations. For instance, the positive coefficients associated with the knowledge stock variables confirm the results from a rich literature pointing to the "standing on the shoulder of the giants"' effect (Caballero and Jaffe, 1993). Participation in international trade has a positive effect on sectoral R&D, confirming positive learning-by-exporting effects.

Tab. 6: PATENT effect of environmental regulation: FE estimation

	(1)	(2)	(3)	(4)	(5)	(6)
1Y Lagged PACE	0.086***	0.075***	0.030**	-	-	-
	(0.02)	(0.02)	(0.02)			
2Y Lagged PACE	-	-	-	0.096***	0.079***	0.002
				(0.03)	(0.02)	(0.02)
Lagged VA	0.061	0.016	-0.045	-0.032	-0.064***	-0.045
	(0.05)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)
Lagged GOVR&D	0.323***	0.178*	-0.073	0.286***	0.079	-0.086
	(0.10)	(0.10)	(0.07)	(0.11)	(0.12)	(0.08)
Lagged PATstock	-	0.521***	0.509***	-	0.518***	0.487***
		(0.10)	(0.08)		(0.09)	(0.09)
Lagged Export	-	-0.012	0.050	-	-0.025	0.105
		(0.08)	(0.07)		(0.09)	(0.09)
Lagged Import	-	-0.296**	-0.277**	-	-0.224*	-0.385***
		(0.12)	(0.11)		(0.13)	(0.15)
Lagged Death rate	-	-	0.024	-	-	0.129
			(0.21)			(0.26)
Lagged Birth rate	-	-	0.275*	-	-	0.483*
			(0.16)			(0.29)
F	6.89***	9.73***	6.40***	10.32***	10.01***	6.70***
Within R-squared	0.37	0.51	0.39	0.39	0.51	0.35
Observations	913	802	639	883	776	587
N.Country-sector	153	136	125	151	135	126

Note: See footnotes of Table 5

External competition, measured by import intensity, has a negative and significant impact both on R&D and patent, confirming the Schumpetrian view of a negative influence of market pressure on innovation. Closure of enterprises, measured by death rate, results in increased R&D intensity. Differently, patent intensity is positively affected by opening of new enterprises. In several specifications the public support of private R&D, measured by the share of public R&D in government budget, has positive effect on private R&D and patent behaviour.

6.3 Endogeneity

Even with all the controls included in the innovation equation, confounding trends in sector-level innovation performance and unmeasured omitted factors that could affect PACE are still reason for concern. Substantively, the endogeneity of the PACE could cause both downward and upward bias in the estimation of PACE effects.

The assumption that omitted common determinants of cost of regulation (PACE) and innovation are time-invariant could be too strong, as these factors are likely to change in time. If this assumption is relaxed, we could not capture these factors with the country-sector fixed effects α_{ij}.

Endogeneity of PACE could also arise in the innovation equation because of reverse causality from innovation to environmental costs. In fact, not only PACE could affect innovation, but also regulation-induced innovation that is designed to lower costs of compliance with regulation will affect PACE (Carrion-Flores and Innes, 2010; Kneller and Manderson, 2012). This two-way relation could bias downward the coefficient of PACE.

Finally, PACE estimates could be biased due to a measurement error problem. PACE is self-reported by firms that have difficulties to identify part of expenditures associated with regulatory compliance in their total expenditures. It could therefore be reported with errors. Moreover, PACE is not adjusted to take into account transfers or subsidies. At the same time some Member Countries use subsidies and refund schemes to protect producers from any negative effect on competitiveness arising from increases in input costs (European Commission 2010).

To overcome potential endogeneity issues we adopt an instrumental variable (IV) approach. PACE is instrumented with a vector of instruments Z that includes the average share of PACE intensity for eight adjacent sectors of the same country excluding the current sector ($PACE/VA^{-j}$) and $PACE/VA^{-j}$ interacted with pre-sample sectoral energy-intensity (year 1996), $EI^{presample}$.[13] In fact, there is a strong correlation between environmental policies applied to different sectors within one country; a sector's PACE intensity is therefore strongly correlated with adjacent sectors' PACE intensity within a country. We complement $PACE/VA^{-j}$ interacted with pre-sample sectoral energy-intensity as regimes of environmental regulation of energy intensity sectors could differ from those of less intensive sectors within the same country, therefore environmental policies of energy intensive sectors could stand out from policies of adjacent sectors. EI is defined as emission-relevant energy use (in tonne of oil equivalent, TOE) over VA. Emission-relevant energy use by sector is the gross energy use excluding non-energy use (e.g. asphalt for road building) and the input for transformation (e.g. crude oil transformed into refined products) of energy commodities, obtained from the WIOD Environmental Accounts database (WIOD, 2012).[14] The identification assumption for all the instruments is that conditional on sectoral Value Added, innovation stock, government R&D support, import intensity, export intensity, enterprises demographic indicators, country-sector fixed effects and time effects, these instruments are strong predictors of sectoral level PACE, but are not correlated with unobserved factors impacting innovation.

We estimate the effect of environmental costs on innovation performance using 2SLS and optimal IV-GMM estimators in the just identifed and the over identified equations, respectively. We also apply limited information maximum likelihood (LIML) which has better small sample properties than 2SLS and optimal IV-GMM estimators with weak in-

[13] Using $PACE/VA^{-j}$ we loose several observations for Estonia, Lithuania, Slovenia, Slovakia and the UK when the PACE data across the sectors are not complete. Due to the nature of $EI^{presample}$ that is time invariant, we could not include it independently in the first stage FE regression as it will be canceled out.

[14] We have minor differences in energy intensity classification comparing to the innovation indicators and PACE. Due to the original classification of the WIOD database "Fabricated metal" is included in the sector 8, rather than in the sector 9. Concerning the sample size, we loose observations on Norway when using EI as an instrument, due to the lack of sector-level data on energy use.

Tab. 7: R&D effect of environmental regulation: First stage results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PACE\_VA^{-j}$	0.209***	0.284***	0.204***	0.268***	-	-	-	-	-
	(0.06)	(0.07)	(0.07)	(0.07)					
Lagged $PACE\_VA^{-j}$	-	-	-	-	0.359***	0.363***	0.374***	0.360***	0.360***
					(0.10)	(0.09)	(0.10)	(0.10)	(0.10)
$PACE/VA^{-j}*EI^{pre}$	-	-0.192**	-	-0.244**	-	-	-	-	-
		(0.09)		(0.11)					
Lagged $PACE/VA^{-j}*EI^{pre}$	-	-	-	-	-	-0.342***	-	-0.334**	-0.334**
						(0.09)		(0.15)	(0.15)
Lagged VA	0.090**	0.164*	0.089**	0.171*	0.103	0.099	0.112	0.103	0.103
	(0.04)	(0.10)	(0.04)	(0.09)	(0.08)	(0.10)	(0.08)	(0.09)	(0.09)
Lagged GOVR&D	-0.238	-0.257	-0.281	-0.294	-0.340	-0.330	-0.387*	-0.371	-0.371
	(0.18)	(0.18)	(0.19)	(0.20)	(0.21)	(0.21)	(0.23)	(0.23)	(0.23)
Lagged R&Dstock	0.220*	0.197	0.244*	0.226	0.175	0.206	0.171	0.217	0.217
	(0.12)	(0.12)	(0.14)	(0.15)	(0.16)	(0.16)	(0.18)	(0.18)	(0.18)
Lagged Export	-	-	0.025	-0.010	-	-	-0.118	-0.107	-0.107
			(0.16)	(0.18)			(0.17)	(0.18)	(0.18)
Lagged Import	-	-	-0.068	-0.207	-	-	-0.298	-0.240	-0.240
			(0.27)	(0.28)			(0.34)	(0.34)	(0.34)
Lagged Death rate	-	-	-0.286	-0.450	-	-	-2.392***	-2.448***	-2.448***
			(0.53)	(0.51)			(0.88)	(0.86)	(0.86)
Lagged Birth rate	-	-	-0.291	0.036	-	-	1.536*	1.584*	1.584*
			(0.66)	(0.66)			(0.89)	(0.89)	(0.89)
F-stat	5.50***	7.97***	4.95***	7.73***	14.78***	16.73***	14.08***	14.53***	14.53***
Within R-sq	0.19	0.23	0.08	0.09	0.20	0.23	0.14	0.15	0.15
C-test of endog.(P value)	0.033	0.342	0.089	0.486	0.029	0.002	0.019	0.000	0.013
Weak-ID test (F instruments)	10.82	13.51	9.17	12.94	13.18	15.99	13.48	12.53	12.53
Stock-Yogo weak ID test critical (val 15% max IV size)	8.96	11.59	8.96	11.59	8.96	11.59	8.96	11.59	8.68
Partial R-squared	0.03	0.06	0.03	0.06	0.07	0.10	0.07	0.09	0.09
AR Weak-ID-robust F (P value)	0.05	0.27	0.10	0.22	0.02	0.01	0.01	0.00	0.00
AR Weak-ID-robust Chi2 (P value)	0.04	0.25	0.09	0.20	0.02	0.01	0.01	0.00	0.00
Over-ID test (P value J-statistic)		0.28		0.25		0.65		0.27	0.28
Observations	641	577	498	480	608	574	509	492	492
N.Country-sector	114	107	108	102	111	104	104	98	98

Note: Coefficient estimates from 2SLS in Columns 1, 3, 5, 7, IV-GMM in Columns 2, 4, 6, 8 and LIML in Column 9.
Country-year fixed effects full and set of time dummies included in all models. All the variables are in logs. Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01.
The data on $PACE/VA^{-j}$ and EI are not complete, therefore we loose some obs. in the IV specifications.
However, we checked that change of sign in IV specifications is not caused by sample reduction, but is due to introduction of IV.

struments (Cameroon and Trevedi, 2010). The first stage attempts to isolate the portion of variation in PACE intensity that is attributable to exogenous environmental expenditures. Predicted PACE from the instruments ignores structural concerns and two-way causality problems that make actual sectoral PACE intensity endogenous. We could be relatively confident that our results reflect causal effects of environmental costs on sectoral innovation performance. Firstly, using a panel data framework we control for sector- and country-specific unobserved characteristics. Moreover, we also control for a level of technological advancements and structural changes within a sector that are commonly accused to generate PACE endogeneity if not explicitly controlled for in a sector-level regulation-innovation model. As well, because we have two instruments for one endogenous variable, we are able to test the joint validity of these instruments, and to show that they pass an over identification test.

Tables 7 and 9 report the results of the first-stage regression between PACE and the set of instruments in the R&D and patent equations, respectively. In both equations the instruments positively correlate with the endogenous PACE. The coefficient

Tab. 8: R&D effect of environmental regulation: Second stage results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instrumented PACE	-0.513*	-0.157	-0.448	-0.125	-	-	-	-	-
	(0.31)	(0.19)	(0.32)	(0.20)					
Instrumented 1Y Lag. PACE	-	-	-	-	-0.277**	-0.318***	-0.403**	-0.475***	-0.542**
					(0.12)	(0.11)	(0.17)	(0.18)	(0.21)
Lagged VA	0.116*	0.067	0.123**	0.093	0.135	0.143	0.156	0.190**	0.163
	(0.06)	(0.09)	(0.06)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Lagged GOVR&D	-0.129	-0.077	-0.040	0.034	-0.170	-0.177	-0.086	-0.077	-0.131
	(0.20)	(0.16)	(0.21)	(0.15)	(0.18)	(0.19)	(0.18)	(0.20)	(0.21)
Lagged R&Dstock	0.746***	0.631***	0.674***	0.563***	0.768***	0.786***	0.665***	0.693***	0.696***
	(0.18)	(0.18)	(0.19)	(0.19)	(0.15)	(0.15)	(0.16)	(0.15)	(0.15)
Lagged Export	-	-	0.413**	0.397**	-	-	0.348**	0.291**	0.301**
			(0.16)	(0.17)			(0.14)	(0.15)	(0.15)
Lagged Import	-	-	-0.161	-0.168	-	-	-0.494***	-0.500***	-0.543***
			(0.22)	(0.25)			(0.17)	(0.19)	(0.20)
Lagged Death rate	-	-	1.589	-0.337	-	-	-0.228	-0.438	-0.666
			(9.12)	(1.98)			(0.68)	(0.72)	(0.79)
Lagged Birth rate	-	-	0.848	-0.372	-	-	0.141	0.254	0.418
			(8.52)	(0.90)			(0.49)	(0.51)	(0.56)
Observations	641	577	498	480	608	574	509	492	492
N.Country-sector	114	107	108	102	111	104	104	98	98

Note: See footnotes of Table 7

of $PACE/VA^{-j}$ and its interaction with the $EI^{presample}$ are strongly significant. The specification tests reported at the bottom of the tables confirm relevance and validity of the instruments. The Kleibergen-Paap test for weak identification‘s F-statistics exceed a widely used rule of thumb equals to 10 (Staiger and Stock 1997) with the exception of specification (3) of Table 7, thus not rejecting the joint significance of excluded restrictions in the first-stage regression. Moreover, F-statistics are above the reported Stock and Yogo (2005) weak ID test critical value (for 10-15% relative IV bias toleration) across different specifications of R&D and patent equations, eliminating the concern that the excluded instruments are weakly correlated with the endogenous regressors (Stock et al. 2002; Stock and Yogo 2005). Another weak-instrument diagnostics that we use is Shea's partial R^2 between PACE and the excluded instruments after controlling for the included instruments in the first-stage regression.The high value in the patent equation indicates that the endogenous regressor is not weakly identified. In the R&D equation the value of partial R^2 is rather low suggesting some need for caution.

The validity of the instruments are tested with Hansen J-test. As the reported p-values of Hansen J-test are greater than 0.05 in all the models, we do not reject the joint null hypothesis that the instruments are valid, i.e. uncorrelated with the error term, and conclude that over identifying restriction is valid. The weak-instrument robust Anderson-Rubin (1949) test statistics always reject the null hypothesis that the coefficients of the one-year lagged PACE in the structural equation are equal to zero, and, in addition, that the overidentifying restrictions are valid. Finally, the C-test rejects the null hypothesis that the the one-year lagged PACE can actually be treated as exogenous in the R&D equation (P value is lower than 0.05). However, exogeneity of one-year PACE is not rejected in the patent equation.

Tab. 9: PATENT effect of environmental regulation: First stage results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1Y Lag. $PACE\_VA^{-j}$	0.446***	0.499***	0.689***	0.673***	-	-	-	-	-
	(0.07)	(0.07)	(0.07)	(0.06)					
2Y Lag.$PACE\_VA^{-j}$	-	-	-	-	0.472***	0.477***	0.575***	0.486***	0.486***
					(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
1Y Lag. $PACE/VA^{-j}*EI^{pre}$	-	-0.101***	-	-0.166*	-	-	-	-	-
		(0.03)		(0.10)					
2Y Lag. $PACE/VA^{-j}*EI^{pre}$	-	-	-	-	-	-0.130**	-	-0.547***	-0.547***
						(0.06)		(0.16)	(0.16)
Lagged VA	0.133	0.151*	0.180*	0.176*	0.073	0.086	0.404***	0.439***	0.439***
	(0.08)	(0.09)	(0.09)	(0.10)	(0.06)	(0.06)	(0.14)	(0.13)	(0.13)
Lagged GOVR&D	-0.123	-0.130	-0.292	-0.277	-0.066	-0.048	-0.198	-0.221	-0.221
	(0.15)	(0.16)	(0.21)	(0.22)	(0.16)	(0.16)	(0.19)	(0.18)	(0.18)
Lagged PATstock	0.360**	0.352**	0.378**	0.390**	0.402**	0.397**	0.406*	0.415*	0.415*
	(0.16)	(0.15)	(0.18)	(0.18)	(0.17)	(0.17)	(0.22)	(0.22)	(0.22)
Lagged Export	-	-	-0.467***	-0.468**	-	-	-0.351*	-0.289	-0.289
			(0.18)	(0.18)			(0.21)	(0.21)	(0.21)
Lagged Import	-	-	0.486	0.491	-	-	0.888**	0.847**	0.847**
			(0.30)	(0.31)			(0.38)	(0.35)	(0.35)
Lagged Death rate	-	-	-0.637	-0.646	-	-	-0.765*	-0.901**	-0.901**
			(0.49)	(0.50)			(0.45)	(0.42)	(0.42)
Lagged Birth rate	-	-	0.427	0.467	-	-	-0.062	0.204	0.204
			(0.43)	(0.42)			(0.48)	(0.40)	(0.40)
F-stat	14.42***	15.34***	10.76***	11.00***	7.41***	7.96***	8.67***	9.10***	9.10***
Within R-sq	0.26	0.29	0.36	0.37	0.24	0.26	0.32	0.36	0.36
C-test of endog.(P value)	0.39	0.26	0.08	0.13	0.02	0.08	0.23	0.15	0.12
F instruments	43.58	30.55	110.75	60.10	41.04	24.83	47.11	33.87	33.87
Stock-Yogo weak ID test critical (val 10% max IV size)	16.38	19.93	16.38	19.93	16.38	19.93	16.38	19.93	19.93
Partial R-squared	0.15	0.18	0.27	0.28	0.16	0.18	0.20	0.25	0.25
P value Anderson-Rubin F-test	0.04	0.01	0.00	0.02	0.00	0.00	0.02	0.00	0.00
P value Anderson-Rubin chi-sq test	0.04	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00
P value J-statistic		0.12		0.48		0.14		0.06	0.06
Observations	828	788	609	592	789	756	613	523	523
N.Country-sector	144	137	122	116	142	135	121	106	106

Note: Coefficient estimates from 2SLS in Columns 1, 3, 5, 7, IV-GMM in Columns 2, 4, 6, 8 and LIML in Column 9.
Country-year fixed effects full and set of time dummies included in all models. All the variables are in logs. Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01.
The data on $PACE/VA^{-j}$ and EI are not complete, therefore we loose some obs. in the IV specifications.

Tab. 10: PATENT effect of environmental regulation: Second stage results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instrumented 1Y Lag. PACE	0.118**	0.124**	0.073**	0.063**	-	-	-	-	-
	(0.06)	(0.05)	(0.03)	(0.03)					
Instrumented 2Y Lag. PACE	-	-	-	-	0.173***	0.152***	-0.045	-0.042	-0.054*
					(0.05)	(0.04)	(0.03)	(0.03)	(0.03)
Lagged VA	0.009	0.004	-0.052	-0.051	-0.075***	-0.073***	-0.008	-0.010	0.021
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
Lagged GOVR&D	0.187**	0.190**	-0.073	-0.082	0.051	0.049	-0.156**	-0.112*	-0.129*
	(0.09)	(0.09)	(0.06)	(0.06)	(0.11)	(0.11)	(0.07)	(0.06)	(0.07)
Lagged PATstock	0.557***	0.548***	0.528***	0.535***	0.533***	0.531***	0.537***	0.518***	0.556***
	(0.09)	(0.09)	(0.07)	(0.07)	(0.10)	(0.10)	(0.09)	(0.08)	(0.09)
Lagged Export	-0.011	0.014	0.079	0.062	-0.057	-0.058	0.083	0.070	0.083
	(0.07)	(0.07)	(0.06)	(0.06)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
Lagged Import	-0.334***	-0.369***	-0.345***	-0.346***	-0.264**	-0.311***	-0.365***	-0.418***	-0.368***
	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)
Lagged Death rate	-	-	-0.028	-0.036	-	-	0.108	-0.052	0.058
			(0.16)	(0.15)			(0.23)	(0.18)	(0.18)
Lagged Birth rate	-	-	0.291*	0.307*	-	-	0.397	0.580**	0.261
			(0.17)	(0.17)			(0.26)	(0.26)	(0.18)
Observations	828	788	609	592	789	756	613	523	523
N.Country-sector	144	137	122	116	142	135	121	106	106

Note: See footnotes to Table 9

Table 8 reports the second-stage estimation results of the R&D equation controlling for potential edogeneity of the PACE variable. Columns 1-4 and 5-9 correspond to the specifications with current and one-year lagged PACE, respectively. The estimates across the specifications noticeably differ from those obtained from the FE regressions. Firstly, controlling for endogeneity changes the interpretation of the lagged impact of PACE on R&D. According to the results of Table 8 the environmental regulation effect becomes negative and significant. Depending on the specification, increasing regulation compliance expenditure by 10 percent leads to 3-5 percent decrease of overall R&D. The effect of R&D thus is overestimated when not accounting for endogeneity. The negative and significant coefficients of one-year lagged PACE are robust to using LIML estimator. The results available from the authors upon request show that environmental regulation proxied by PACE does not affect R&D after one-year period. Also the current PACE effect is statistically not different from zero with the exception of Column 1 where it is negative and significant.

The results of the patent equation using one- and two-years lagged PACE variables are reported in Table 10. The one-year lagged PACE remains positive and strongly significant with the similar magnitude to the FE estimation. Other things equal, an additional 10 percent of regulation compliance expenditure increases number of patent applications by approximately 0.8 percent in the one-year period. However, when controling for PACE endogeneity the two-years lagged effect of environmental regulation on patent becomes insignificant. We omit for brevity the estimation results of R&D and patent equations with PACE variable included beyond the one-year lag and the two-years lag period, respectively, as they don't confirm the regulation effect. [15] With the exception of public R&D the effects of the other control variables are robust to change from the FE to IV estimations in both. [16]

Taking together the results of R&D and patent equations, we conclude that environmental regulation lead to an increase of patent applications in the short-run. The firms promptly react to environmental regulation with patents. We believe that these results could be driven by increased incentives of manufacturing firms for patent protection of green innovations. Under a stringent environmental regulation patenting of such projects is likely to give a firm a first-mover competitive advantages. However, by committing resources to comply with regulation, the firm reduces overall R&D expenditure. The IV results of both innovation equations highlight the upward bias of the lagged PACE coefficients in the FE estimation.

Our results on R&D effect are thus not in line with those of earlier findings of Jaffe and Palmer, 1997 for the U.S. and Hamamoto, 2006 for Japan, where more PACE are found

[15] The results are available from the authors upon request.

[16] Surprisingly, the effect of public R&D becomes negative in several specifications of the patent equation. One possible explanation of this result is that the public R&D data lacks sectoral variation and thus does not always allow to capture a public R&D impact in the sectoral level analysis.

to bring about significant R&D enhancement effects both in the short- and the medium-term. As regards to patents, the number of previous findings state that environmental regulation positively impacts overall environmental patents at the sector-level in the U.S (Brunnermeier and Cohen, 1998) and specific environmental patents in OECD countries (Vries and Withagen, 2005; Popp, 2006; Johnstone, Hasic and Popp, 2008). Differently from these authors, we show on the sample of European countries that environmental regulation results in enhancement of overall patent activity (and not only environmental patents).

7 Environmental regulation and productivity

7.1 Empirical strategy

Having found a link between environmental regulation stringency, proxied by PACE, and innovations, the paper further examines the relations between regulation stringency and productivity. It is important to note that environmental regulation affects productivity through a number of channels. On one hand, the firm may need to use additional inputs, such as labour, materials or capital to comply with environmental requirements (the direct effect). Consequently, a raise of production costs could result in a negative impact on productivity in the short run. On the other hand, as was confirmed in the previous section, environmental regulation would affect the knowledge stock that in turn, could, show up in productivity (the indirect effect). The latter effect is likely to appear in the medium-long run.

In view of multiple channels through which environmental regulation affects productivity, the link between the former and the latter is traditionally modelled through a reduced-form equation, where productivity is commonly measured by TFP or, more rarely, by LP (for example, Gray and Shadbegian, 1993, 2001; Lanoe et al., 2008). In a reduced-form equation a magnitude of the coefficient associated with environmental regulation captures the overall effect of environmental regulation that operates through the different channels mentioned above. Particularly, a positive coefficient of environmental regulation variable would mean that an induced innovation effect, if any, outweighs additional input costs caused by environmental requirements to such an extent that productivity is enhanced, thus supporting the “strong" Porter Hypothesis.

Following the previous literature and assuming a Cobb-Douglas three factor inputs production function our first reduced-form model relating the level of TFP with environmental regulation and other controls reads as follows: [17]

$$TFP_{ijt} = \beta_1 \ln ER_{ijt-q} + \gamma \ln \mathbf{X}_{ijt-1} + \alpha_{ij} + \mu_t + \epsilon_{ijt} \tag{5}$$

[17] We also employed Labor Productivity as a productivity indicator. The results using are qualitatively similar and available from the authors upon request.

Where TFP is the total-factor productivity, as desribed in Appendix A, in country i, sector j and time t, respectively. ER denotes the environmental regulation proxied by PACE. As the productivity impact of environmental regulation is likely to be dynamic, the next issue to be discussed is the time setting. Given that ER contributes to productivity growth, the obvious question is, how soon we can expect the environmental regulation effect. With regards to direct effect of environmental regulation through additional input costs it is likely to be prompt. What concerns the induced R&D effect, an empirical literature suggest that R&D brings about productivity growth at a lag of one to three years (for example, Griffith et al., 2004). Moreover, as established in the previous section, the impact of environmental regulation on R&D is likely to be lagged as well. Thus we include ER in the reduced-form productivity equation with different lags - from one to four years.

To control for factors that could affect sectoral productivity we include the vector of covariates $\mathbf{X}$ that contains enterprises birth rate (Birth) and death rate (Death), import penetration (Import), export intensity (Export), and Value Added (VA).

The productivity impact of environmental regulation is conditional on plants survival. Stringent regulation can results in the closure of some plants. Not accounting for survivorship the true productivity effect can be understated. To control for the effect of sector structural change due to enterprises creations, deaths or relocations on productivity of a sector we incorporate enterprises birth (Birth) rate and deaths rates (Death) indicators in the equation.

We also include import intensity (Import) as the role of import penetration is stressed in the cross-country productivity growth literature. The literature suggests a variety of mechanisms by which trade may affect productivity growth: among them spillovers of technology from the reverse engineering of imported goods, increased product market competition, and larger market size (Griffith et al., 2004)

We supplement the vector of controls with export intensity (Export) which controls for a sector‘s participation in foreign trade. As suggested by learning-by-exporting hypothesis, strong competition abroad could encourage productivity improvements (Grossman and Helpman,1991).

Finally, as larger industries are likely to have greater absolute levels of PACE, we include Value Added (VA) as a scaling factor.

The variables in $\mathbf{X}$ are lagged one year to avoid two-way causation with productivity. Other than learning-by-exporting effect, the causality can run from productivity to export through the self-selection effect: higher productivity could cause higher exporting of the firm. Productivity decrease of the local producers could bring into the country the foreign producers, thus, increasing import intensity. Moreover, the productivity enhancement could cause boost of production scale, thus the causality between productivity and VA could also be bidirectional.

Next, we move to growth specifications, where productivity growth (rather than levels) is regressed against its determinants and fixed effects. The model reads as follows:

$$\Delta TFP_{ijt} = \beta_1 \ln ER_{ijt-q} + \gamma \ln \mathbf{X}_{ijt-1} + \alpha_{ij} + \mu_t + \epsilon_{ijt} \tag{6}$$

Where ΔTFP is “raw" TFP growth indicator as described in Appendix A. [18]

In the TFP growth model we supplement the variables in $\mathbf{X}$ with measure of TFP growth at the frontier (TFP growth frontier) and the measure of distance from the technological frontier (TFP gap) that are found to be an important determinant of productivity growth (Nicoletti and Scarpetta, 2003; Griffith et al., 2004). The frontier country is defined as the country with the highest TFP level in sector j and time t. The assumption is that, within each sector and year, the level of efficiency, among the other factors, depends on technological and organisational transfer from the technology-leader country. This variable aims at capturing the link between TFP growth in the "catching-up" country with the extent of innovation and knowledge spillovers which are taking place in the technologically most advanced country. In particular, we assume that TFP growth in the frontier country leads to faster TFP growth in follower countries by widening the production possibility set. We also include a technological gap that is defined as a distance between TFP level of sector j in country i and the frontier country in time t. We assume that this variable captures the extent to which TFP growth in a specific country can be explained by the adoption of more efficient existing technologies. The assumption here is that the larger the technology gap, the higher the potential gains from adopting more efficient, internationally available, technologies and consequently the faster the rate of TFP growth.

An important concern in estimating the cross-country sector-level productivity models is the choice of the fixed effect. Apparently, inclusion of country-sector specific effects α_{ij} would be preferred to control for country-sector time-invariant determinants of productivity levels and growth rates that are also likely to be correlated with the regressors. For example, country-sector fixed effects could account for omitted market structure and other specific country-sector characteristics. On the other hand, using country-sector specific effects we concentrate on variation of a certain country-sector over time, therefore the parameters are identified only through the within dimension of the data. As one could see from the analysis of variance in Table A.1 of Appendix, TFP indicator (in levels) has very low within variation (close to zero), therefore will be very imprecisely estimated from FE regression. Therefore to estimate TFP model in levels we also use

[18] To confirm the robustness of our results, we also use the quality-adjusted TFP growth indicator, which, according to theory, is a better indicator of disembodied technological change than “raw" TFP. The TFP growth indicator is constructed using the quality-adjusted input indices, as described in (A.3) of Appendix A. However, the disadvantage of using quality-adjusted TFP growth indicator is that we loose some observations due to lack of data availability of quality adjusted indices. The results, available from the authors upon request, are qualitatively similar to the one using the ‘raw" TFP growth indicator.

an alternative specification that assumes two separate fixed effects, i.e. country effects α_i and sector effects α_j. The latter specification mostly relies on the variation across countries and sectors that could be fruitfully exploited with our TFP data. Moreover, separate country and sector fixed effects account for a variety of omitted variables in the productivity equation such as the level of education and skills of labor force, own-sector regulatory environment etc. To summarise, the specification including country-sector specific effects α_{ij} is desirable on theoretical grounds, since it minimizes the possibility of unmeasured sector-country characteristics biasing the other coefficients. Therefore, we use it for estimation of TFP growth model. However, due to low within variation of TFP level indicator the specification including separate country- and sector-effects seems to be more appropriate. All the equations include time effects μ_t that control for common European-wide aggregate shocks of productivity, and an error term ϵ_{ijt}.

Finally, it is important to keep in mind that due to productivity data availability we carry out estimations for eleven European countries (out of seventeen for which PACE data are available): Czech Republic, Finland, Hungary, Lithuania, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden and the United Kingdom over the period 1997-2007. Therefore, the results are not directly comparable with innovation model results that are estimated for seventeen countries. However, the results available from the author upon request show that innovation model results are robust to using the country sample of productivity model.

7.2 Estimation results

As a starting point we verify the impact of generic innovation on TFP levels from the two different specifications described above. As innovation proxies we use the fitted values of R&D and patent variables predicted from the innovation equation 2.[19] The results of the FE estimation of TFP level model, reported in Columns 1-2 of Table A.2 of Appendix, demonstrate striking results not favouring the idea that innovation drives the productivity growth. The coefficients associated with the fitted value of the one-year lagged overall R&D are insignificant, whereas patent variable is negative and significant.[20] Judging from this model, higher R&D investments over time do not bring any productivity gain to a certain country-sector, whereas more patent applications decrease its productivity. Columns 3-4 of Table A.2 present an alternative specification with country- and sector-fixed effects α_i and α_j included separately. Using overall variation of the data (rather than only within variation) in the latter model we found a positive effect of generic innovation on productivity, confirming that sectors investing more intensively in R&D

[19] Bootsrapped standard errors are applied to properly account for problem of generated regressor.

[20] The results are robust to using different lags of R&D and patents, using original R&D and patent values (rather than predicted), as well as R&D and PATENT stock variable (rather than gross R&D and PATENT).

Tab. 11: TFP level impact of environmental regulation

	FE				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1Y Lagged PACE	-0.008	-0.007	-	-	-0.055**	-0.088***	-	-
	(0.01)	(0.01)			(0.02)	(0.03)		
2Y Lagged PACE	-	-	-0.006	-0.001	-	-	-0.050**	-0.086***
			(0.01)	(0.01)			(0.02)	(0.03)
Lagged Import	-0.024	-0.019	-0.022	-0.047	-0.053	0.036	-0.048	0.028
	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)
Lagged Export	0.022	-0.006	0.003	-0.016	0.118	0.148*	0.133	0.158*
	(0.05)	(0.06)	(0.06)	(0.06)	(0.09)	(0.08)	(0.09)	(0.08)
Lagged Death rate	-	0.035	-	0.146*	-	-0.055	-	-0.108
		(0.04)		(0.09)		(0.18)		(0.22)
Lagged Birth rate	-	-0.027	-	-0.150	-	0.274	-	0.508*
		(0.09)		(0.11)		(0.22)		(0.26)
Lagged VA	-	-0.012	-	-0.017	-	0.116***	-	0.000
		(0.02)		(0.03)		(0.04)		(0.00)
F	6.02***	5.38***	6.94***	6.03***	19.75***	21.67***	21.48***	21.36***
R-squared	0.18	0.21	0.16	0.17	0.84	0.85	0.84	0.84
Observations	530	476	458	432	530	476	458	432
N.Country-sector	96	95	96	95	96	95	96	95

Note: Country-sector fixed effects in Columns 1-4, separate country- and sector-fixed effects in Columns 5-8. Set of time dummies included in all models. All the variables are in logs.
Robust standard errors (clustered on the sector-country unit) in parentheses. * p<.1, ** p<.05, *** p<.01.
Within R-squared are reported in Columns 1-4.

are more productive than those investing less. The findings of no link between generic innovation and productivity from the FE model confirms our previous remark about low within variation of TFP indicator and irrelevance of FE model for verification of the link between environmental regulation and productivity in the Porter Hypothesis context using our sample.

Having established relations between generic innovation and TFP level from two different models, we move to a reduced-form model where we regress TFP on one- and two-years lagged PACE and the set controls. Table 11 reports the results. We use the model with separate country- and -sector fixed effects as a preferred specification of TFP level model (Columns 5-8) , but also report the results of the FE model for comparability (Columns 1-4) . The FE results provide an evidence of negligible effect of environmental policy on TFP. Differently from the FE results, the OLS model with separate country- and -sector fixed effects reveals an adverse effect of environmental policy on TFP in one- and two-years lagged period. The negative effect is robust to adding and omitting various controls (such as Export and Import intensity, Death and Birth rate). Other things equal, increasing regulation compliance expenditures by 10 percent results in about 0.3-0.9 percent decrease of TFP. Thus, from the the preferred specification of TFP level model we conclude that despite of positive effect of generic innovation, stringent regulation results in a lower productivity. Hence, an induced innovation effect, if any, is not large enough to overcome additional input costs required for regulation compliance, consequently, resulting in a productivity drop.

Tab. 12: TFP growth impact of environmental regulation

	(1)	(2)	(3)	(4)	(5)	(6)
1Y Lagged PACE	-0.001	0.004	0.004	-	-	-
	(0.00)	(0.00)	(0.00)			
2Y Lagged PACE	-	-	-	-0.003	0.002	0.001
				(0.00)	(0.00)	(0.00)
TFP growth at the frontier	0.273***	0.233**	0.232**	0.169	0.226**	0.226**
	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Lagged TFP gap	-0.172*	-0.078***	-0.078***	-0.038	-0.070**	-0.071**
	(0.09)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Lagged Death rate	-	0.039	0.039	-	0.086***	0.087***
		(0.04)	(0.04)		(0.03)	(0.03)
Lagged Birth rate	-	-0.064	-0.064	-	-0.055	-0.052
		(0.05)	(0.05)		(0.05)	(0.05)
Lagged Import	-	-0.021	-0.020	-	0.003	0.006
		(0.03)	(0.03)		(0.03)	(0.03)
Lagged Export	-	0.039	0.040	-	0.032	0.035
		(0.03)	(0.03)		(0.02)	(0.02)
Lagged VA	-	-	0.003	-	-	0.008
			(0.01)			(0.01)
F	3.69***	3.03***	2.85***	3.84***	7.27***	6.65***
Within R-squared	0.15	0.16	0.16	0.09	0.18	0.18
Observations	542	476	476	470	432	432
N.Country-sector	98	95	95	98	95	95

Note: Country-sector fixed effects and time dummies included in all models. All the variables are in logs. Robust standard errors (clustered on the sector-country unit) in parentheses. * p<.1, ** p<.05, *** p<.01.

Table 12 reports the estimation results of TFP growth model. Regardless of the controls used, PACE variable always remains insignificant. Moreover, Columns 5-6 of Table A.2 of Appendix show no link between generic R&D and TFP growth. [21]

The coefficients associated with other controls used in the the productivity regressions are in line with the expectations. For instance, participation in international trade has a positive effect on sectoral TFP level and growth, confirming positive learning-by-exporting effects. TFP gap term enters TFP growth equation negatively and is significant, indicating that within each industry the countries that are further behind the frontier experience higher rates of productivity growth. The TFP growth at the frontier is positive and significant. This implies that TFP growth in the frontier country leads to faster TFP growth in follower countries. Finally, the coefficients associated with import penetration and structural changes are not significant.

7.3 Endogeneity

The potential endogeneity of PACE could be also a concern in the productivity equation. Firstly, in the FE specification the assumption that omitted common determinants of cost of regulation (PACE) and productivity at the country-sector level are time-invariant could be too strong, as these factors are likely to change over time. If this assumption is relaxed, we can not capture these factors with the country-sector fixed effects α_{ij} (and neither with α_i and α_i). Secondly, endogeneity of contemporaneous PACE could arise

[21] The results available from the authors upon request show that no impact of generic R&D and PACE on TFP growth is also robust to relaxing the fixed effects.

in productivity equation for the likely reverse causality. Firms' political pressures to change regulations are an important potential source of reverse causality. In particular, if firms respond to negative productivity shocks by "lobbying" for relaxing of environmental regulations inverse causality would entail positive correlations between productivity and environmental regulation indicators. Therefore, the impacts of environmental regulations on productivity could be overestimated. Finally, similar to the innovation equation, productivity impact of environmental regulation could be biased due to PACE measurement error.

To overcome the potential endogeneity issues we adopt an instrumental variable (IV) approach similar to the one used in innovation equations.We estimate the effect of environmental costs on innovation performance using 2SLS and optimal IV-GMM estimators in the just identifed and the over identified equations, respectively, with country, sector and time fixed effects (alternatively, we estimates specifications with country-sector and time fixed effects). Similarly to the innovation equation, the vector of instruments Z includes an average share of PACE intensity for eight adjacent sectors of the same country excluding the current sector ($PACE/VA^{-j}$) and its interaction with pre-sample sectoral energy-intensity (year 1996), $EI^{presample}$. The identification assumption is that conditional on import intensity, export intensity, enterprises demographic indicators, fixed effects and time effects, the instruments are strong predictors of sectoral level PACE intensity, but are not correlated with unobserved factors impacting productivity.

Table 13 reports the results of the first-stage IV regression. We present the results of two alternative specification of TFP model in levels - the FE and the OLS -in Columns 1-4 and 5-8, respectively. The results of the TFP growth model are reported in Columns 9-10. The coefficient of $PACE/VA^{-j}$ and $EI^{presample}$ are strongly significant across all the specifications. The specification tests reported at the bottom of the tables confirm relevance and validity of the instruments. The Kleibergen-Paap test for weak identification F-statistics considerably exceed a widely used rule of thumb equals to 10 (Staiger and Stock 1997), thus not rejecting the joint significance of excluded restrictions in the first-stage regression. Moreover, F-statistics are higher than the reported Stock and Yogo (2005) weak ID test critical value (for 10% relative IV bias toleration) across different specifications (with the exception of Columns 7-8) eliminating the concern that the excluded instruments are weakly correlated with the endogenous regressors (Stock et al. 2002; Stock and Yogo 2005). Another weak-instrument diagnostics that we use is Shea partial R2 between PACE and the excluded instruments after controlling for the included instruments in the first-stage regression. Shea partial R2 are relatevely large, thus indicating that the endogenous regressor is not weakly identified.

The validity of the instruments are tested with Hansen J-test. As the reported p-values of Hansen J-test are greater than 0.05 in all the models, we do not reject the joint null hypothesis that the instruments are valid, i.e. uncorrelated with the error term, and

Tab. 13: TFP effect of environmental regulation: First stage results

	TFP level								TFP growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1Y Lag $PACE/VA^{-j}$	0.683***	0.580***	-	-	0.477***	0.530***	-	-	0.677***	0.560***
	(0.08)	(0.09)			(0.10)	(0.10)			(0.08)	(0.09)
1Y Lag $PACE/VA^{-j}$*EI^{pre}	-	-0.508***	-	-	-	0.150***	-	-	-	-0.564***
		(0.19)				(0.04)				(0.18)
2Y Lag $PACE/VA^{-j}$	-	-	0.616***	0.509***	-	-	0.400***	0.456***	-	-
			(0.08)	(0.10)			(0.11)	(0.10)		
2 Y Lag $PACE/VA^{-j}$*EI^{pre}	-	-	-	-0.501**	-	-	-	0.135***	-	-
				(0.21)				(0.03)		
Lagged Import	0.707**	0.793***	0.867***	0.868***	-0.430***	-0.380***	-0.403**	-0.367**	0.633**	0.697**
	(0.28)	(0.27)	(0.33)	(0.31)	(0.16)	(0.14)	(0.16)	(0.14)	(0.28)	(0.28)
Lagged Export	-0.904***	-0.852***	-0.406	-0.430	0.034	0.021	0.073	0.059	-0.890***	-0.817***
	(0.27)	(0.26)	(0.36)	(0.35)	(0.15)	(0.14)	(0.14)	(0.13)	(0.27)	(0.26)
Lagged Death rate	-1.106	-1.075	-1.202***	-1.241***	-0.373	-0.242	-0.812*	-0.671	-1.038	-1.000
	(0.88)	(0.88)	(0.28)	(0.30)	(0.91)	(0.90)	(0.43)	(0.45)	(0.89)	(0.89)
Lagged Birth rate	1.308	1.293	1.322**	1.244**	1.095	0.969	1.758***	1.671***	1.301	1.298
	(1.16)	(1.16)	(0.53)	(0.54)	(1.14)	(1.15)	(0.56)	(0.57)	(1.14)	(1.13)
Lagged VA	0.339**	0.447***	0.397*	0.452**	0.587***	0.610***	0.642***	0.656***	0.333**	0.456***
	(0.13)	(0.14)	(0.20)	(0.18)	(0.10)	(0.09)	(0.10)	(0.09)	(0.14)	(0.15)
F-stat	11.36***	13.04***	16.72***	16.03***	91.87***	85.92***	125.72***	117.01***	10.97***	11.83***
Adj. R-sq	0.40	0.42	0.34	0.35	0.90	0.90	0.90	0.90	0.41	0.43
C-test of endog.(P value)	0.201	0.410	0.328	0.749	0.025	0.042	0.017	0.049	0.301	0.156
F instruments	74.02	51.04	53.05	34.21	21.79	19.72	14.48	14.69	73.05	51.31
Stock-Yogo weak ID test critical (val 10% max IV size)	16.38	19.93	16.38	19.93	16.38	19.93	16.38	19.93	16.38	19.93
Partial R-squared	0.28	0.30	0.23	0.25	0.15	0.12	0.12	0.11	0.28	0.30
P value Anderson-Rubin F-test	0.04	0.14	0.28	0.32	0.26	0.19	0.13	0.17	0.65	0.75
P value Anderson-Rubin chi-sq test	0.04	0.12	0.27	0.30	0.24	0.16	0.11	0.14	0.64	0.74
P value J-statistic		0.28		0.21		0.18		0.21		0.51
Observations	467	467	413	413	476	476	432	432	467	467
N.Country-sector	86	86	76	76	86	86	76	76	86	86

Note: Coefficient estimates from 2SLS in Columns 1, 3, 5, 7, 9; IV-GMM in Columns 2, 4, 6, 8, 10. Full set of time dummies included in all models. Country-sector fixed effects in Columns 1-4 and 9-10. Country- and sector-fixed effects in Columns 5-8. All the variables are in logs. Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01. Within R2 in Columns 1-4 and 9-10.

Tab. 14: TFP effect of environmental regulation: Second stage results

	TFP level								TFP growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Instrumented 1Y Lag. PACE	-0.020*	-0.014*	-	-	0.037	0.018	-	-	-0.003	-0.004
	(0.01)	(0.01)			(0.03)	(0.03)			(0.01)	(0.01)
Instrumented 2Y Lag. PACE	-	-	-0.013	-0.005	-	-	0.078	0.038	-	-
			(0.01)	(0.01)			(0.06)	(0.04)		
TFP growth at the frontier	-	-	-	-	-	-	-	-	0.241**	0.245***
									(0.10)	(0.09)
Lagged TFP gap	-	-	-	-	-	-	-	-	-0.084***	-0.085***
									(0.03)	(0.03)
Lagged Import	-0.014	-0.022	-0.041	-0.072	0.085	0.057	0.094	0.059	-0.018	-0.017
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)	(0.07)	(0.03)	(0.03)
Lagged Export	-0.012	-0.001	-0.020	0.001	0.141	0.111	0.147	0.125	0.036	0.035
	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)	(0.08)	(0.09)	(0.08)	(0.03)	(0.02)
Lagged Death rate	0.027	0.029	0.136*	0.148*	-0.036	-0.103	-0.013	-0.087	0.035	0.035
	(0.04)	(0.04)	(0.08)	(0.08)	(0.24)	(0.18)	(0.22)	(0.21)	(0.04)	(0.04)
Lagged Birth rate	-0.012	-0.023	-0.130	-0.153	0.149	0.197	0.196	0.289	-0.055	-0.054
	(0.08)	(0.08)	(0.10)	(0.10)	(0.25)	(0.21)	(0.27)	(0.23)	(0.05)	(0.05)
Lagged VA	-0.007	-0.008	-0.012	-0.019	0.039	0.041	0.005	0.025	0.007	0.007
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)	(0.05)	(0.04)	(0.01)	(0.01)
Observations	467	467	413	413	476	476	432	432	467	467
N.Country-sector	86	86	76	76	86	86	76	76	86	86

Note: See footnotes to Table 13

conclude that over identifying restriction is valid. The weak-instrument robust Anderson-Rubin (1949) test statistics does not reject the null hypothesis that the coefficients of the one- and two-years lagged PACE in the structural equation are equal to zero, and, in addition, that the overidentifying restrictions are valid. Finally, the C-test rejects the null hypothesis that the the one- and two-years lagged PACE can actually be treated as exogenous in Columns 5-8 of the productivity model (P value is lower than 0.05). Thus we conclude that the endogeneity of the lagged PACE is likely to be a concern in the productivity model.

In fact, the results of the second-stage IV regression, presented in Table 14, do not confirm the findings of the previous section about a negative link between environmental regulation and productivity. Accounting for PACE endogeneity in our preferred specifications of TFP level model, we found that environmental regulation has negligible effect on productivity regardless of the lag structure used (Columns 5-8). The same results are confirmed from the TFP growth model estimation (Columns 9-10). [22] Finally, the results of the FE estimation suggest that ER decreases productivity in the one-year period (Columns 1-2). However, we believe that these results should be taken with care, as it was demonstated before, the FE model does not support as whole the "innovation channel" of productivity growth.

Taking together the productivity models results, we conclude thus that stringent environmental regulation does not harm productivity either in one-year or in two-years period. Rather, the overall productivity effect is neutral. We found some evidence that not accounting for PACE endogeneity the estimates of productivity effect could be downward biased. On the whole, negligible productivity effect of ER may arise as consequence of induced innovation effect that helps to neutralise the negative effect of additional compliance costs. Therefore, the results more favour rather than disprove the "strong" Porter Hypothesis.

7.4 Robustness checks

In this subsection we consider the robustness of our results to several concerns. For coherence with the TFP level model, we would like to verify sensitivity of the innovation results to using the model with alternative set of fixed effects. In particular, in Table 16 we present the estimation results of innovation IV model where we relax the fixed effect α_{ij} and assume two separate fixed effects, i.e. country effect α_i and sector effect α_j. The results are very much in line with our previous findings on innovation effect of environmental regulation. In particular, they suggest that increased PACE adversely affects current R&D and increases patent application in one-year period. However the

[22] The results available from the authors upon request show that the PACE beyond the one-year lag has no effect on TFP growth in the IV regression.

Tab. 15: R&D and patent effect of environmental regulation: OLS with α_i and α_j

	R&D				PATENT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PACE	0.056	0.031	-	-	-	-	-	-
	(0.07)	(0.08)						
Lagged PACE	-	-	0.018	0.005	0.048*	0.003	-	-
			(0.07)	(0.07)	(0.03)	(0.03)		
2Y Lagged PACE	-	-	-	-	-	-	0.054	-0.033
							(0.03)	(0.04)
Lagged VA	0.067	0.102	0.107	0.137	0.115**	0.142***	0.069	0.217***
	(0.07)	(0.15)	(0.12)	(0.14)	(0.04)	(0.05)	(0.05)	(0.07)
Lagged GOVR&D	-0.338**	-0.344**	-0.307*	-0.369**	0.149	-0.118	0.039	-0.089
	(0.14)	(0.15)	(0.17)	(0.15)	(0.10)	(0.07)	(0.11)	(0.10)
L.ln_RDstock2	0.506***	0.575***	0.511***	0.583***	-	-	-	-
	(0.06)	(0.07)	(0.06)	(0.07)				
Lagged INNOstock	-	-	-	-	0.666***	0.658***	0.743***	0.672***
					(0.19)	(0.19)	(0.17)	(0.20)
Lagged Export	0.032	0.014	0.073	0.038	0.103	0.152	0.121	0.173
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.12)	(0.11)	(0.12)
Lagged Import	-0.280*	-0.227	-0.233	-0.181	-0.005	-0.036	-0.050	-0.015
	(0.16)	(0.21)	(0.18)	(0.20)	(0.12)	(0.11)	(0.13)	(0.12)
Lagged Death rate	-	2.660**	-	2.353*	-	0.533	-	0.474
		(1.23)		(1.39)		(0.53)		(0.44)
Lagged Birth rate	-	-1.611	-	-0.083	-	0.233	-	0.695
		(1.40)		(1.46)		(0.29)		(0.49)
F	126.39***	143.17***	147.88***	166.51***	238.48***	379.47***	280.68***	342.81***
R-squared	0.95	0.95	0.95	0.95	0.97	0.98	0.97	0.98
Observations	626	498	603	504	802	639	776	587
N.Country-sector								

Note: Coefficient estimates from the second-stage FE regression. Country- and sector-fixed effects and set of time dummies included in all models. All the variables are in logs.
Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01.

positive patent effect vanishes after one year and becomes negative in two-years period.

Another robustness check is related to lags of productivity effect of environmental regulation. As was mentioned before, innovation could be translated into productivity improvements with long lags. Moreover, the returns on environmental innovation are likely to be further lagged, as they regard mostly newly created markets which are small and fast growing. Short run returns from eco-innovations could be negligible, while medium-long run returns could be very high. Thus, we test the impact of three and four years lagged regulation variable in the productivity equation. Estimation results are reported in Table 17. Similar to the one- and two-years productivity effects, they are negative and significant (Columns 5 and 7 of Table 17). However, the negative effect of environmental regulation on TFP is not robust to controlling for PACE endogeneity. The effect of PACE with longer lags becomes negligible when using IV (Columns 6 and 8 of Table 17), thus confirming that environmental regulation does not distort productivity the medium-run.

Tab. 16: R&D and patent effect of environmental regulation: IV with alternative fixed effects (α_i and α_j)

	R&D				PATENT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrumented PACE	-0.348	-1.230**	-	-	-	-	-	-
	(0.52)	(0.51)						
Instrumented 1Y Lag. PACE	-	-	-0.189	-0.999	0.137**	0.097*	-	-
			(0.93)	(0.68)	(0.06)	(0.06)		
Instrumented 2Y Lag. PACE	-	-	-	-	-	-	-0.075*	-0.174*
							(0.05)	(0.09)
Lagged VA	0.129	0.378	-0.004	0.420	0.069	0.078	0.233***	0.294***
	(0.20)	(0.27)	(0.30)	(0.30)	(0.05)	(0.06)	(0.08)	(0.09)
GOVR&D	0.062	-0.083	0.188	-0.486	-0.051	-0.084	-0.114	-0.181*
	(0.18)	(0.32)	(0.54)	(0.47)	(0.09)	(0.08)	(0.09)	(0.11)
Lagged R&Dstock	0.610***	0.743***	0.512***	0.683***	-	-	-	
	(0.14)	(0.14)	(0.17)	(0.16)				
Lagged PATstock	-	-	-	-	0.620***	0.763***	0.710***	0.873***
					(0.20)	(0.18)	(0.20)	(0.18)
Lagged Export	0.313*	0.500**	0.217	0.511**	0.125	0.044	0.143	0.077
	(0.17)	(0.23)	(0.23)	(0.24)	(0.11)	(0.11)	(0.11)	(0.11)
Lagged Import	-0.481	-0.834**	-0.214	-0.582	-0.003	0.063	-0.036	-0.009
	(0.33)	(0.41)	(0.44)	(0.39)	(0.11)	(0.10)	(0.11)	(0.11)
Lagged Death rate	1.049	0.646	2.565**	1.176	0.428	0.079	0.485	0.182
	(0.83)	(1.11)	(1.26)	(1.28)	(0.51)	(0.42)	(0.42)	(0.41)
Lagged Birth rate	-0.044	0.493	-1.304	0.382	0.212	0.214	0.662	0.704
	(0.74)	(1.00)	(1.34)	(1.14)	(0.34)	(0.31)	(0.49)	(0.51)
Adjusted R-squared	0.94	0.89	0.94	0.90	0.98	0.98	0.98	0.98
Observations	501	481	515	497	612	594	560	535

Note: Coefficient estimates from the second-stage IV regression. Country- and sector-fixed effects and set of time dummies included in all models. All the variables are in logs.
Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01.

Tab. 17: TFP impact of environmental regulation with longer lags (three and four years)

	specfications with α_{ij}				specfications with α_i and α_j			
	(1)	(2 IV)	(3)	(4 IV)	(5)	(6 IV)	(7)	(8 IV)
3Y Lagged PACE	-0.001	-0.003	-	-	-0.069**	0.013	-	-
	(0.01)	(0.01)			(0.03)	(0.02)		
4Y Lagged PACE	-	-	-0.005	-0.003	-	-	-0.091***	0.026
			(0.01)	(0.01)			(0.03)	(0.05)
Lagged Import	-0.027	-0.048	-0.117*	-0.095*	0.054	0.065	0.036	0.060
	(0.07)	(0.06)	(0.06)	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)
Lagged Export	-0.013	-0.015	-0.005	0.017	0.164*	0.130*	0.169**	0.126
	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)	(0.08)	(0.08)	(0.08)
Lagged Death rate	0.131	0.081	0.600***	0.546***	1.052**	1.138**	0.686	0.907*
	(0.15)	(0.13)	(0.17)	(0.14)	(0.51)	(0.51)	(0.51)	(0.53)
Lagged Birth rate	0.075	0.092	0.134	0.077	-0.270	-0.409	0.895*	0.497
	(0.15)	(0.13)	(0.15)	(0.12)	(0.42)	(0.40)	(0.49)	(0.52)
Lagged VA	-0.018	-0.018	-0.061	-0.080*	0.085*	0.023	0.085	0.005
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)
Adjusted R-squared	0.13	0.12	0.18	0.17	0.84	0.83	0.83	0.81
Observations	360	360	293	292	360	360	293	293

Note: Set of time dummies included in all models. All the variables are in logs. Within R2 in Columns 1-4
Robust standard errors (clustered on the sector-country unit) in parentheses.* p<.1, ** p<.05, *** p<.01.

8 Conclusive remarks

This paper has provided econometric evidence on the relations between environmental regulation and competitiveness, as captured by innovation activity and productivity, in a panel of industrial sectors across seventeen European countries over the period of 1997-2009. The advantage of our approach mainly concerns providing a combined assessment of both innovation and productivity impact of environmental regulation that allows to obtain a complete and robust evidence on the “strong” Porter effect for the sample of European countries over the last decades. Unlike the few previous studies focusing on Europe and investigating the effect of environmental regulation on green innovation and performance (De Vries and Withagen, 2005; Constantini and Crespi, 2008; Johnstone et al., 2010), we look at overall competitiveness and innovation that are the most relevant indicators for the “strong” PH. This approach allows us to account for potential opportunity costs of environmental regulation and induced innovations.

Another important distinction of the paper is that it explicitly accounts for potential edogeneity of PACE in the context of environmental regulation-economic performance nexus using IV approach. To our knowledge, with the exception of a few papers (De Vries and Withagen, 2005, Carrion-Flores and Innes, 2010, Kneller and Manderson, 2012) the existing literature generally does not explicitly account for the endogeneity problem of PACE variables in the PH context. Our results prove that not controlling for endogeneity of the PACE variable lead to a biased estimates and in some cases reverse the interpretation of the environmental regulation effect on economic performance and competitiveness.

Regarding the R&D effect of environmental regulation, we find a positive and statistically significant effect from the FE estimation. However, the sign of the estimated innovation effect changes when when properly controlled for PACE endogeneity. Using IV approach, environmental regulation are proved to lower overall R&D in the one-year period. Other things equal, raise of environmental expenditure by 10 percent results in about 3 percent of R&D decrease. Therefore, combined with the evidence of limited availability of financial resources devoted to R&D activities, we confirm that induced R&D performed to obtain environmental innovation come at the opportunity cost and crowd-out general R&D employed in other projects.

Despite the overall R&D decline, we find a positive and statistically significant patent effect of environmental regulation in the one-year period. Other things equal, an additional ten percent of regulation compliance expenditure increase number of patent applications by approximately one percent. This finding is robust for the inclusion of a series of control variables and controlling for endogeneity of PACE. European firms thus are likely to increase number of patent applications in respond to strict environmental regulation with the one-year lag. However, as the whole innovation process from R&D investment to patent application takes time and induced R&D could be translated into patents with more than one year lag, one can argue that R&D related to induced patents took place before an introduction of stringent environmental regulation. Moreover, judging from our estimation results, there is no evidence of positive immediate effect of environmental regulation on R&D. Therefore, we interpret the positive patent effect as an evidence of more productive R&D in terms of successful innovations or increasing demand for patent protection, rather than an evidence of increased number of new R&D projects. We believe that a higher number of patent applications is likely to be associated with expansion of innovative environmental technologies, that become more beneficial under strict environmental regulation as they help to reduce compliance costs. Moreover, firms could seek to protect these new environmental technologies with patent to get a first-mover advantage.

Comparing with the earlier sector-level studies, our results on adverse R&D effect of environmental regulation obtained for the sample of the European countries contrast with the results of Jaffe and Palmer (1997) for the U.S. and Hamamoto (2006) for Japan, where more PACE are found to bring about significant R&D enhancement effects both in the short- and the medium-term. We believe that neglecting the issue of PACE endogeneity, along with the other factors, is the reason for this discrepancy. With regards to the previous country-level studies on Europe, focusing on specific environmental patents, rather than overall patent behaviour, they generally conclude that environmental patents positively responds to environmental policy (Vries and Withagen, 2005; Popp, 2006; Johnstone, Hasic and Popp, 2008). However, they do not consider the opportunity costs of environmental innovation. Therefore, our results are not directly comparable with these studies.

Having found a link between environmental stringency and overall innovation, the paper further examines the relations between environmental regulation and productivity. Overall, our analysis confirms a positive contribution of generic R&D to productivity. Assuming that positive induced innovations effect on productivity, if any, will show up in the medium-long run due to the fact that the impact of environmental regulation on R&D is likely to be lagged and that R&D, in turn, could bring about productivity growth at a lag of several years. Thus, we consider the policy variable with different lags - from one- to four-years period. Not accounting for PACE endogeneity we found that environmental regulation adversely affects productivity. Other things equal, spending one additional percent of total costs on regulation compliance results in about two-three percent decrease of measured TFP from one- to four-years lagged period. However, the negative effect on TFP does not show up when we apply IV approach, highlighting that the estimates of productivity effect are likely to be downward biased in the OLS model. The overall productivity effect of regulation becomes neutral more favouring rather than disproving the “strong” Porter Hypothesis. In fact, the result of a negligible impact on productivity is compatible with the presence of positive induced R&D effect that helps to mitigate additional input cost spent on regulation compliance. Despite of the fact that firms invest less in R&D, as proved in our estimation, we could assume that they invest "smarter" and thus become more efficient. On the other hand, high direct costs imposed on regulated firms are likely to be the reason of no productivity gain and negligible impact of environmental regulation on productivity that we observe on the sample of European countries.

The evidence that more stringent environmental regulation does not affect productivity don't support the conclusions of the early U.S. studies (Gray and Shadbegian (1993, 2001)) about depressing effect of environmental regulation on industrial productivity. Our results also do not concur with the results of the sector-level productivity investigations of Hamamoto, 2006 for Japan, Lanoie, Patry and Lajeunesse, 2008 for Canada and Yang, Tseng, Chen, 2012 for Taiwan that conclude that stringent environmental policy spur productivity growth. Again, we believe that one of the reason for this disagreement is the treatment of PACE endogeneity.

Apparently, the limitation of our analysis is that due to limited PACE availability we could not consider a number of large economies of the EU that widely apply various regulatory instruments for pollution control and natural resource management, such as Germany, France and Italy. Moreover, due to productivity measures availability our productivity analysis is based on the investigation of the few countries of interest (Czech Republic, Finland, Hungary, Netherlands, Slovenia, Spain, Sweden, United Kingdom, Lithuania, Poland, Portugal) and relatively short time period, that does not allow to consider increasing number of recent environmental policies, that entered into force after 2006 as consequence of EU-wide environmental strategy. Therefore, as soon as new PACE and productivity data become available, it can be very interesting to estimate innovation and productivity impacts of environmental regulation on a large sample of countries and over a longer period. This could be a topic for further research.

Furthermore, given some inconsistency in our findings for innovation and productivity response, further research is needed before these results can be considered complete and conclusive. In order to understand better the implications of the stringent environment policy on industrial competitiveness of the EU countries, it would be interesting to disentangle the contribution of environmental regulation to growth of green innovations and other innovations, and to study, subsequently, how different type of innovations contribute to productivity growth across the European countries. Unfortunately, the sector-level environmental innovation data is missing for the European countries and thus do not allow to carry our the structural analysis of pollution control and abatement efforts on economic performance of the European manufacturing industries.

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A Construction of productivity indicators

Assuming a Cobb-Douglas three factor inputs production function, the level of TFP is defined as the portion of output not explained by the amount of factor inputs used in production :

$$TFP_{ijt} = \ln GO_{ijt} - \alpha_{ijt} \ln L_{ijt} - \beta_{ijt} \ln I_{ijt} - (1 - (\alpha_{ijt} + \beta_{ijt})) \ln K_{ijt} \qquad \text{(A.1)}$$

Where TFP denotes the level of TFP, GO is gross output, K is net capital stock, L is labor hours (of total engaged) and I is intermediate inputs (including energy, service and material inputs). All the monetary variables are expressed in constant prices and PPPs. Concerning the inputs weights, there are two widely used approaches to estimate α and β. On the one hand, we can assume that input markets are competitive and that there are no sources of rents to the firm (e.g., assume constant returns to scale and perfect competition). This implies that the coefficients α and β are the shares of revenue received by each of the factors. On the other hand, one can assume that the coefficients are (roughly) constant across entities and estimate them via a regression. We follow the first approaches and compute α and β as the labour input and intermediate input shares in total costs, respectively. The assumption of constant return to scale implies that sum of input shares is equal to 1. To compute the labour input share we adjust the labour compensation by the ratio of total employment to total employees to account for the compensation of self-employed. They are not registered in the National Accounts and, therefore, not included in the labor compensation indicator. To obtain the capital input share, we calculate the nominal capital value as the residual of gross output minus labour compensation in nominal values. If the residual and therefore the share in total output are negative, we use a simple heuristic rule suggested in O'Mahony and Timmer (2009) and constrain capital compensation to be non-negative, setting it to zero.

To calculate quantities of input and output, nominal values are deflated by industry-specific relative prices (PPPs). PPPs are output- and various types of inputs-specific and are available for all the EU countries at a detailed EU KLEMS industry level from the GGDC Productivity Level database (Inklaar and Timmer (2008)).The limitation of these price indices is that they are available only for the year 1997. Therefore, to extrapolate PPPs for the period 1995-2007 we back and update PPPs of 1997 using price deflators for each country relative to the US, which is a benchmark country, at a detailed industry level. For example, PPPs for VA is extrapolated as follows:

$$PPP_{ijt} = \frac{VA\_P_{ijt}/VA\_P_{ij1997}}{VA\_P_{usjt}/VA\_P_{usj1997}} * PPP_{ij1997} \tag{A.2}$$

Where VA_P is VA deflator. Similar methodology is used for extrapolation of output and intermediate inputs PPPs. However, we follow a different procedure to obtain capital inputs due to the lack of the capital input deflators. We adjust the capital stock (in constant 1997 prices) obtained from the EU KLEMS with the PPPs for capital service. The capital PPPs is not available for Greece, Lithuania, Latvia, Poland, therefore, for these countries we apply PPPs for GO. [23]

As argued in the literature, a major issue in the construction of TFP measures is the need to control for the quality of inputs. TFP estimates constructed from the measures of labor and capital inputs that are not adjusted for the skill composition of the workforce, on one hand, and for the composition of the capital stock inputs, on the other hand, capture both disembodied and embodied components of technological progress (see Nicoletti and Scarpetta, 2003; O'Mahony and Timmer, 2009). The disembodied component captures technological and organisational improvements that increase output for a given amount of quality and compositionally adjusted-inputs. The second component of technological progress is termed embodied and proxies for the improvements in the productive capacity due to shifts to higher quality factor inputs (Nicoletti and Scarpetta 2003). Therefore, any "raw" TFP indicator captures both embodied and disembodied aspects of technical change, whereas a quality-adjusted TFP indicator measures productivity obtained through technological and efficiency improvements.

[23] The drawback is that we don't adjust the capital stock for possible price changes in the benchmark country.

We calculate the quality-adjusted TFP growth as the real growth of output minus a weighted growth of inputs services:

$$\Delta \widetilde{TFP}_{ijt} = \Delta \ln \tilde{G}O_{ijt} - \bar{\alpha}_{ij}\Delta \ln \tilde{L}_{ijt} - \bar{\beta}_{ij}\Delta \ln \tilde{I}_{ijt}$$
$$-(1-(\bar{\alpha_{ij}}+\bar{\beta}_{ij}))\Delta \ln \tilde{K}_{ijt} \tag{A.3}$$

Where $\tilde{G}O_{ijt}$ denote gross output index, $\tilde{L}_{ijt}$, $\tilde{I}_{ijt}$ and $\tilde{K}_{ijt}$ are labor services, intermediate input and capital services indices, respectively, and $\bar{\alpha}_{ij}$ and $\bar{\beta}_{ij}$ are the average inputs shares over two periods computed as following:

$$\bar{\alpha}_{ij} = 0.5(\alpha_{ijt} + \alpha_{ijt-1}) \tag{A.4}$$

$$\bar{\beta}_{ij} = 0.5(\beta_{ijt} + \beta_{ijt-1}) \tag{A.5}$$

Similarly, we define the "raw" TFP growth indicator, using the output and inputs variables as defined in (2).

We also need to address an issue of sectoral aggregation in our data. The EU KLEMS dataset breakdown differs from the nine-sectors PACE classification that we use [24]. We therefore need to merge some of the sub-sectors to conform with the required classification. We collapse “Chemicals and chemical” and “Rubber and plastic products” in the sector 6. As well, we collapse “Machinery and equipment”, “Electrical and optical equipment”, “Transport equipment” and “Manufacturing ned; recycling” to obtain sector 9. Still, some inconsistency remains between productivity and PACE measures sectoral breakdown. Firstly, in PACE sectoral breakdown “Fabricated metal” is included in sector 9, while in the EU KLEMS it is reported together with “Basic metal” and could not be isolated and attributed to sector 9. We correct the nominal input and output values associated with sectors 8 and 9 by computing “Fabricated metal” value share in

[24] The EU KLEMS provides 28 manufacturing sub-sectors break-down

aggregated metal sector from the EU KLEMS (March 2008 Release, which reports these two sub-sectors separately). The only (minor) problem that remains and, unfortunately, could not be solved is that while "Recycling" is excluded from sector 9 for PACE, it is included and could not be isolated from sector 9 in the EU KLEMS. But we believe that as the sector 9 is composed of several sub-sectors, the contribution of "Recycling" to its productivity is smoothed.

For aggregation of the inputs and output indices across sub-sectors we use Tornqvist quantity index (as suggested by O'Mahony and Timmer 2009).Unfortunately, we can't adjust the indices for the inconsistently between quality-adjusted TFP and PACE measures in sectors 8 and 9 classification, so we should keep it in mind the minor difference in sectoral breakdown when using quality-adjusted TFP growth measure in our analysis.

Tab. A.1: Variance analysis of the main variables

Variable		Mean	St.deviation
ln_PACE	overall	3.308	1.660
	between		1.541
	within		0.472
ln_R&D	overall	2.835	2.158
	between		2.134
	within		0.421
ln_PAT	overall	1.854	1.916
	between		1.888
	within		0.324
TFP	overall	1.156	0.437
	between		0.434
	within		**0.068**
TFP growth	overall	0.013	0.042
	between		0.011
	within		0.040

Tab. A.2: Impact of generic innovation on TFP

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged R&D^{PRED}	-0.068	-	0.100***	-	-0.001	-
	(0.06)		(0.02)		(0.00)	
Lagged PAT^{PRED}	-	-0.078*	-	0.070**	-	0.000
		(0.04)		(0.03)		(0.00)
TFP growth at the frontier	-	-	-	-	0.179	0.210**
					(0.11)	(0.10)
Lagged TFP gap	-	-	-	-	0.020***	0.007
					(0.01)	(0.01)
Lagged VA	-0.055	-0.018	-0.076	-0.001	-	-
	(0.04)	(0.03)	(0.05)	(0.03)		
Lagged Death rate	0.328	0.167	0.613	0.100	-0.023	0.058
	(0.25)	(0.24)	(0.89)	(0.78)	(0.08)	(0.06)
Lagged Birth rate	-0.378*	0.115	0.374	0.603	-0.003	-0.042
	(0.21)	(0.22)	(0.83)	(0.60)	(0.09)	(0.07)
Lagged Import	-0.032	-0.087	0.084	0.020	-0.008***	-0.005
	(0.12)	(0.08)	(0.06)	(0.05)	(0.00)	(0.00)
Lagged Export	-0.030	-0.043	0.046	0.150***	0.006**	0.003
	(0.07)	(0.06)	(0.05)	(0.04)	(0.00)	(0.00)
R-squared	0.23	0.20	0.84	0.84	0.16	0.18
Observations	296	354	296	354	296	354
N.Country-sector	84	86	84	86	84	86

Note: Country-sector fixed effects in Columns 1-2, 5-6, separate country and sector fixed effects in Columns 3-4. Set of time dummies included in all models. All the variables are in logs. Bootsrapped standard errors in parentheses. * p<.1, ** p<.05, *** p<.01
Within R2 in Columns 1-2, 5-6.

Environmental Policy Indicator: Application of a three-level random intercept model

Abstract

This paper presents a novel approach, inspired by the literature on multilevel latent models and Item Response Theory (IRT), to assessing and comparing countries' environmental and energy policy portfolios and performance. We use data on energy efficiency policy targeting industrial sectors in 27 EU countries between 2004 and 2009 and rank countries with respect to their ability to implement policy over time. Unlike previous contributions in this respect, our model accounts for the inherent difficulty of a given policy instrument mix. Moreover, the model is extended to deal with the longitudinal nature of our data and to adjust the country ranking as a result of economic and institutional observables which are likely to affect policy design and implementation.

Contents

1 Introduction

Addressing pressing climate concerns by limiting bluehouse gas emission, supporting renewable energy production and increasing energy efficiency is one of the five objective of Europe 2020, the sustainable growth stategy that EU member states launched in 2010 as a response to the recent global economic crisis.[1] To support these goals, which have been declined in national targets for each member state, a number of environmental and energy policies have been put in place so far and will be implemented in the years to come. A major challenge researchers and policy makers alike have been struggling with is the assessment of such policies and how countries are performing in this respect.

Appropriately describing and understanding the past performance of countries with respect to energy and environmental policies, and their ability to implement a more or less complex portofolio of policy instruments, is a crucial step in ensuring that future interventions are drafted in a sound and cost-effective way. An in-depth analysis in this respect is however currently missing, partly due to lack of appropriate data, but also to more complex conceptual problems, as pointed out in Brunel & Levinson (2013).

Specifically, quantitative assessments of environmental and energy policy implementation are often charachterized by a series of important shortcomings. First, to address climate and energy concerns countries can choose from a wide array of policy instruments, each of which is charachterized by a different level of effectiveness, dynamic efficiency and political acceptability (Fisher & Newell, 2008). Second, the ability of countries to implement certain low cost options might depend crucially on some “initial condition” or on some time varying charachteristics, such as the level of energy efficiency of the economy, the age of capital, the industrial composition or the political framework. For example, more polluting countries can possibly reap the lower hanging fruits, while countries which are already on the path of supporting efficiency and blue energy might need to resort to more costly options.

This paper contributes to the literature by providing a novel approach to assessing and comparing countries’ environmental policy portfolios and per-

[1]The Europe 2020 strategy includes five main objectives: ensuring 75 % employment of 20/64-year-olds; Getting 3 % of the EU’s GDP invested into research and development; limiting bluehouse gas emissions by 20 % or even 30 % compared to 1990 levels, creating 20 % of EU energy needs from renewables and increasing energy efficiency by 20 %; reducing school dropout rates to below 10 %, with at least 40 % of 30/34-year-olds completing tertiary education; ensuring 20 million fewer people are at risk of poverty or social exclusion.

formance. This method, inspired by the literature on multilevel latent models and Item Response Theory (IRT), results in a ranking of European countries with respect to their ability to implement energy and environmental policy which accounts for the inherent difficulty of a given policy instrument mix. Moreover, the model is extended to deal with the longitudinal nature of our data and to adjust the country ranking as a result of country-specific observables which are likely to affect policy implementation, such as the level of energy efficiency or other institutional characteristics.

The rest of this paper is organized as follows. Section 2 provides a review of the available literature and summarizes the contributions of this paper. Section 3 presents our data and empirical model. Section 4 summarizes the empirical results and presents the ranking of countries in each particular year over the period 2004-2009 in terms of their ability to implement environmental policies which accounts for the complexity of the policy mix put into place and the effect of economic and institutional observables. Section 5 concludes with a summary of main results, policy implications and a list of future research needs.

2 Literature Review

A number of previous contributions set forth to building environmental and energy policy indicators to help reseachers and policy makers alike address important questions such as the impact of policy on innovation, on energy efficiency, on growth and on overall economic performance. Brunel & Levinson (2013) provide a comprehensive review of the litearature in this respect. In doing so, they identify the main conceptual issues that plague previous efforts to create an index of energy and environmental policy stringency.

First, creating a reliable indicator is challenging due to the issue of multidimensionality. Governments regulate various aspects of energy production and environmental protection, namely air, water, toxic chemicals, but also energy efficiency and renewable energy production. Moreover, policy instruments can be aimed at regulating pollution directly, thorough either a command-and-control or a market-based approaches. In addition, environmental and energy policies *per se* can be combined with policies aimed at addressing the knowledge market failure externality, and stimulate the creation and diffusion of less polluting technologies.[2] Such heterogeneity in policy responses and in the sectors targeted makes it hard to build an indicator that is at the same time comprehensive and detailed enough to capture changes in all different aspects of a country's policy portfolio.

Second, while policy makers and resarchers ideally would want to measure the effect of policy on other important outcome variables such as industry location, trade patters, economic growth or knowledge transfer, the variables measuring the stringency of environmental regulation are plagued by simultaneity and endogeneity. One must therefore bear in mind that policies are often jointly determined with other outcome variables and that they themself are not exogenous, but are the result of forces within the economic system.

Finally, some countries/sectors might have a "comparative" advantage with respect to other in implementing strict environmental policy. This might be due to their industrial composition, but also to the vintage of capital or to the fact that they are more polluting to begin with. This gives them the option to implement low-cost high-reduction (or high-efficiency improvement) policies.

Given the diversity of policies portfolios implemented and the heterogeneity across sectors, many have resorted to *ad hoc* datasets which are tailored to answering a specific research question (Jeppsen & Folmer, 2001). However, as pointed out in Carraro *et al.* (2010) greater accuracy comes at the cost of limited comparability and results across studies focusing on different sectors are often not comparable.

Popular proxies for regulatory stringency are data on private sector abatement expenditures. Such data inform on the level of financial effort a given firm/sector has to face to comply with given standards (Berman & Bui, 2001; Hamamoto, 2006; Jaffe & Palmer, 1997; Lanjouw & Mody, 1996). The justification of this indicator is based on the assumption that profit maximising firms typically face marginal abatement costs that are increasing in pollution abatement. However, pollution abatement costs (PACs) are plagued with reverse causality issues. Moreover, if the data is used at the aggregated level,

[2] Environmental (and energy) policy directly targets the environmental externality by regulating pollutants or emissions. On the one hand, command-and-control policy instruments include mandates and standard, and are charactherized by the fact that they set a minimum requirement for firms to comply with. On the other hand, market-based approaches such as taxes and permits allow firms to respond more flexibly to comply with the regulation. Conversely, technology policy targets the knowledge market failure and supports R&D in blueer and more efficient technologies with, among other options, research subsidies and investments.

such as sectors or countries, changes in PACs might result from changes due to unobserved heterogeneity rather than from changes in regulatory stringency. Finally, in the presence of market of behavioral failues abatement expenditures no longer successfully measure the level of regulatory pressure (Berman & Bui, 2001).

Other popolar indicators of choice include reductions in emissions or pollutants or indicators based on energy use (Cole & Elliot, 2003; Gollop & Roberts, 1983). Aggregated over firms or sectors, these variables are also likely to mirror changes such as factor prices rather than regulatory stringency. When they are used at the disaggregated level, it is often hard to build indicators that can be used in cross sectoral or cross country analysis due to the heterogeneity of the regulated pollutants.

Changes in regulation-based measures have also been used to judge the level of policy stringency (Popp, 2003, 2010). However, proxies based on normative prescriptions do not account for the level of actual enforcement of a given policy and might also be subjects to issues of reverse causality (Brunnermeier & Cohen, 2003; Shimshack & Ward, 2005).

To compare different sectors and countries, an extensive literature resorts to building general composite indexes through the use of aggregation techniques. The data used to this end include information on the presence or absence of a given policy (0-1 indicators) or scores from surveys of government officials or business leaders (Kellenberg, 2009; Tobey, 1990). When using data from surveys, these indexes tend to capture only perceived, and not actual, regulatory stringency (Johnstone *et al.* , 2010).

(Johnstone *et al.* , 2010) and Vona & Nicolli (2012) propose two different aggregate indicators to measure the level of renewable environmental policies in European countries. First, an average-based indicator which uses information on the timing of adoption of a given policy instrument (effectively, an average - TO DELETE THIS WORD dummy variables indicators equal to zero before the instrument is put into place and equal to one afterwards). Second, a more complex indicator is built using principal component analysis relying both on dummy variables and on intensity of specific policy instruments such as Renewable Energy Certificates of Feed-in Tariffs. This approach is more sophisticated than previous efforts in this sense, since the factor loadings resulting from the PCA in Vona & Nicolli (2012) can be interpreted as importance weights which vary by item/policy. However, in this approach countries are all considered equal, namely they have the same propensity to implement any of the policy instruments. Focus only on renewable energy policy. [3]

In this paper, we apply an approach inspired by Item Response Theory to study and describe the level of environmental policy within a set of countries. Our contribution is novel in several respects. First, while the basic approach we propose has been applied in the statistical literature of scoring, its application to the context of environmental policy is new. Second, we extend the basic IRT model to a multilevel framework which is consistent with the nature of the policy data available. Third, our approach allows to attribute different weights or difficulty levels to the different policy instrumentes included in the policy portfolio. Thus, our assessment is conditional on the specific complexity of each country's policy portfolio. Fourth, we combine the multilevel IRT model with a latent regression, thereby allowing each country scores to be conditioned on observed country's characteristics.

In the next Section, we briefly summarize the data used in this paper and present our extended multi-level model.

3 Empirical Strategy

The data we use in this application is the one developed within Rubaskina *et al.* (2013), namely a set of policy indicators for a sample of 27 countries within the years 2004-2009. The data is extracted from the Mesures d'Utilisation Rationnelle de l'Energie (MURE) database, which collects information on the adoption time of selected energy efficiency policy measures for the rational use of energy and for the promotion of end-use renewables in the manufacturing sector of EU Member States. The information is provided by national energy agencies or institutes according to harmonised guidelines (Schlomann and Eichhammer 2011). The MURE includes the national policies that have macro-economic impact, imposing a quality threshold which eliminates low-impact policies. Distinguished feature of MURE is "semi-quantitative" impact evaluation of each policy, that is reported at three levels - igh ediumr ow The category is based on the percentage of overall final energy or electricity savings and carbon dioxide emissions reductions achieved over a given time-frame

[3]Moreover, as demonstrated in Ferrari & Salini (2011) the presence of dummy variables should require Categorical Principal Components Analysis (CATPCA) which is not based on the assumption of linear correlation.

by a sector or, in case of fuel substitution and CHP, on the percentage of primary energy consumption reduction. Table shows the energy and CO2 savings thresholds defined for each level of "semi-quantitative" impact. [4]

Policy Impact in term of Energy and CO2 savings of the sector	Energy and CO2 savings of the sector	Weight
Low	$< 0.1\%$	1
Medium	0.1- 0.5%	2
High	$\geq 0.5\%$	3

We use information on five different environmental policy instruments derived from the MURE: Regulatory Policies, Voluntary Measures, Financial Instruments, Fiscal/tax reductions and Information/Education, Regulatory policies include norms and standards, such as energy efficiency levels for various kinds of equipments and production processes or products, which often are based on the phase out of old technologies. Voluntary agreements include the creation of industry/government cooperation, as well as various industry initiative aimed at promoting higher levels of energy efficiency. Financial instruments include investment subsidies and low interest loans, as well as incentives and subsidies for energy audits. Fiscal measure include tax credit and exemptions which are put in place to target higher levels of efficiency within industrial sectors. Information and education policies and measure are aimed at increasing the awareness of technology users and their knowledge about opportunities for efficiency improvements.

We construct an ordered categorical variable for each policy instrument by weighting each policy according to the "semi-quantitative impact" evaluation and counting the weighted policies of a particular type which are active in any given year. To weight the policies by impact evaluation we recoded impact evaluation into the numerical weights of 1, 2, or 3, with each correspond to high, medium and low impact, respectively. The advantage of using the weighted count as the policy proxy is that it captures stringency and level of implementation of each policy under consideration. Thus, our policy proxies account for number of different policies in place, as well as their stringency,

[4]The estimated energy savings (fuels and electricity) and carbon dioxide emissions reductions achieved over a given time-frame is reported when a quantitative evaluation is available for a measure. If no quantitative evaluation is available, or in addition to the quantitative evaluation, a qualitative expert judgement of measure impact in terms of energy and CO2 savings is reported (high/medium/low)

Table 1: Summary statistics of the policy variables: initial vs final categorisation

	Variable	Unit	Original scale		New scale	
			Min.	**Max**	**Min.**	**Max**
1	Regulatory Policies	Weight. count	0	12	0	3
2	Financial Instruments	of policy programs	0	17	0	5
3	Voluntary Measures		0	13	0	4
4	Fiscal/tax reductions		0	16	0	2
5	Information/Education		0	13	0	4
6	Energy taxation	Effective tax rate, TOE/EURO	52,6	259,2	0	4

that we believe is an improvement upon the earlier environmental policy indicators (e.g. Vona & Nicolli (2012)).

We complimented the policy variables constructed from MURE with a variable of energy tax policy, increasingly favoured in European countries. [5] Energy tax is a tax on energy products used for both transport and stationary purposes and CO2 emission. As a proxy of energy tax we use effective energy tax rate, defined as energy tax revenues over final energy consumption in EURO/TOE, obtained from the EUROSTAT (EUROSTAT, 2013). For consistency with the other ordinal policy variables, we turn our tax variable into categories from 0 to 4. The higher is the value of a numerical measure, the higher category is assigned.

[5] We don't use the energy tax policy information in MURE as it is very incomplete, records for many countries that use energy tax as a policy instrument are missing. Hence we use the data from the EUROSTAT

mandatory	2004	2005	2006	2007	2008	2009
Austria	0	0	0	0	0	0
Belgium	1	1	1	1	1	1
Bulgaria	0	0	0	0	0	3
Cyprus	0	0	0	2	2	2
Czech Rep	1	1	1	1	1	1
Estonia	0	0	0	0	0	0
Finland	2	2	2	2	2	2
France	1	1	1	1	1	1
Germany	2	2	2	3	3	3
Greece					3	3
Hungary	0	0	0	0	0	0
Ireland	0	0	0	0	2	2
Italy	3	3	3	3	3	3
Latvia	1	1	1	1	1	1
Lithuania	0	0	0	0	0	0
Luxembourg	0	0	0		0	0
Malta			0	0	0	0
Netherlands	1	1	1	1	1	1
Norway	0	0	0	0	0	0
Poland	0	0	0	0	0	0
Portugal	1	1	1	1	1	1
Romania	0	0	0	0	3	3
Slovak Republic	1	2	2	2	2	2
Slovenia	0	0	0	0	0	0
Spain	0	0	0	0	0	0
Sweden	0	0	0	0	1	1
United Kingdom	2	2	2	2	2	2

(a)

Voluntary	2004	2005	2006	2007	2008	2009
Austria	0	0	0	0	0	0
Belgium	3	3	3	3	3	3
Bulgaria	0	0	0	0	1	1
Cyprus	0	0	0	0	0	0
Czech Rep	0	0	0	0	0	0
Estonia	1	1	1	1	1	1
Finland	3	3	3	4	4	4
France	4	4	4	2	2	2
Germany	3	3	3	4	4	4
Greece					0	0
Hungary	0	0	0	0	0	0
Ireland	2	2	3	3	3	3
Italy	0	0	0	2	2	2
Latvia	0	0	0	0	0	0
Lithuania	0	0	0	1	1	1
Luxembourg	3	3	3		3	3
Malta			0	0	0	0
Netherlands	4	4	4	4	4	3
Norway	0	2	2	2	2	2
Poland	0	0	0	0	0	0
Portugal	0	0	0	0	0	0
Romania	0	0	0	0	1	1
Slovak Republic	0	0	0	0	1	1
Slovenia	0	0	0	0	0	0
Spain	0	1	1	0	0	0
Sweden	1	3	3	3	3	4
United Kingdom	4	4	4	4	4	4

(b)

Financial	2004	2005	2006	2007	2008	2009
Austria	0	0	0	0	0	0
Belgium	1	1	1	1	1	1
Bulgaria	2	2	2	5	5	5
Cyprus	4	4	4	4	4	4
Czech Rep	1	1	2	1	1	1
Denmark						
Estonia	0	0	0	0	2	2
Finland	5	5	5	5	5	5
France	3	3	3	2	2	2
Germany	4	3	3	3	4	4
Greece					3	4
Hungary	2	2	1	1	1	1
Ireland	0	0	2	2	2	2
Italy	2	3	3	5	5	5
Latvia	0	0	0	0	1	4
Lithuania	2	2	2	2	2	2
Luxembourg	0	0	0		0	0
Malta			1	1	1	5
Netherlands	4	4	3	3	3	3
Norway	4	4	4	3	3	3
Poland	0	0	0	0	2	2
Portugal	3	3	0	0	0	0
Romania	2	2	2	3	3	4
Slovak Republic	3	3	3	5	4	4
Slovenia	2	2	2	2	5	5
Spain	5	5	5	4	2	2
Sweden	0	0	0	0	0	0
United Kingdom	5	5	5	5	5	5

(c)

Fiscal	2004	2005	2006	2007	2008	2009
Austria	0	0	0	0	0	0
Belgium	1	1	1	1	1	1
Bulgaria	0	0	0	0	0	0
Cyprus	0	0	0	0	0	0
Czech Rep	0	0	0	0	0	0
Estonia	1	1	1	1	1	1
Finland	1	1	1	1	1	1
France	0	0	0	0	0	0
Germany	0	1	1	1	1	1
Greece					0	0
Hungary	0	0	0	0	0	0
Ireland	0	0	0	0	0	0
Italy	0	0	0	2	2	2
Latvia	0	0	0	0	0	0
Lithuania	0	0	0	0	0	0
Luxembourg	0	0	0		0	0
Malta			0	0	0	0
Netherlands	2	2	2	2	2	2
Norway	0	1	1	1	1	1
Poland	0	0	0	0	0	0
Portugal	0	0	0	0	1	1
Romania	0	0	0	0	0	0
Slovak Republic	0	1	1	1	1	1
Slovenia	0	0	0	0	0	0
Spain	0	0	0	0	0	0
Sweden	0	0	0	0	1	1
United Kingdom	2	2	2	2	2	2

(d)

Info/Education	2004	2005	2006	2007	2008	2009
Austria	1	2	2	2	2	2
Belgium	0	0	1	1	1	1
Bulgaria	0	0	0	0	0	0
Cyprus	2	2	3	3	3	3
Czech Rep	0	0	0	0	0	0
Estonia	0	0	0	1	1	1
Finland	3	4	4	4	4	4
France	1	1	1	1	1	1
Germany	1	1	1	2	2	2
Greece					0	1
Hungary	0	0	0	0	0	0
Ireland	2	2	3	3	3	3
Italy	0	0	0	0	0	0
Latvia	0	0	0	0	0	0
Lithuania	1	1	1	1	1	1
Luxembourg	0	0	0		0	0
Malta			0	0	0	0
Netherlands	0	0	0	0	0	1
Norway	1	1	1	1	1	1
Poland	1	1	1	1	1	1
Portugal	0	0	0	0	1	1
Romania	0	0	0	0	0	0
Slovak Republic	2	2	2	2	3	3
Slovenia	0	0	0	0	0	0
Spain	0	2	2	0	0	0
Sweden	0	0	0	0	0	2
United Kingdom	4	4	4	4	4	4

(e)

Energy tax	2004	2005	2006	2007	2008	2009
Austria	2	2	2	2	2	2
Belgium	1	1	1	1	1	1
Bulgaria	0	0	0	0	1	1
Cyprus	2	2	2	2	2	2
Czech Rep	0	1	1	1	1	1
Estonia	0	0	0	0	1	1
Finland	1	1	1	1	1	1
France	2	2	2	2	2	3
Germany	3	3	3	3	3	3
Greece	1	1	1	1	1	2
Hungary	0	1	1	1	1	1
Ireland	2	2	2	2	2	3
Italy	4	4	4	4	4	4
Latvia	0	0	0	0	0	0
Lithuania	0	0	0	0	1	1
Luxembourg	3	3	3	3	3	3
Malta	1	2	2	4	2	3
Netherlands	3	3	3	3	4	4
Norway	2	3	3	3	3	3
Poland	0	1	1	1	1	1
Portugal	2	2	2	2	2	2
Romania	0	0	0	0	0	0
Slovak Republic	0	0	0	1	1	1
Slovenia	2	2	2	2	2	3
Spain	2	2	2	2	2	2
Sweden	3	3	3	4	4	3
United Kingdom	4	4	4	4	4	4

(f)

Figure 1: Policy variables distributions (a) Mandatory policies, (b) Voluntary policies, (c) Financial policies, (d) Fiscal policies, e) Information/Education, f) Energy taxation

Given the nature of our data, the most appropriate model would allow the treatment of many interrelated variables with the aim of summarizing data and highlighting possible latent factors. Our starting point lies in the Rasch model (Rasch, 1980), a statistical model originally developed as a psychometric tool for the social sciences. This model has been applied in psychology, but also medicine and education. Bacci (2012) and Bacci & Bartolucci (2012), for example, apply it to the scoring of quality of life; Bacci & Caviezel (2011) use it to score teaching evaluation. Recently the model also found applications in organizational and management studies and specifically applied to financial issues (Soutar & Cronish-Ward, 1997), marketing and consumer behavior (Fischer *et al.* , 2006; Salzberg & Sinkovics, 2006) and to tourism management (Oreja-Rodriguez & Yanes-Estevez, 2007). Ferrari *et al.* (2005) explore its validity and constraints as a tool to quantify the vulnerability of degree of historical-architectonical buildings in Northern Italy. Murray & Mills (2012) applies as similar methodology to the scoring of energy insecurity in the United States.

The traditional Rasch model, developed for dichotomous data, is based on the assumption that the object of the study is a latent variable in which two different entities interact: the subjects under consideration and the different "items" which are observed for each of the subjects. In this framework, the probability of observing a given item (or positive response) for any given individual is a decreasing function of item difficulty/complexity and an increasing function of the subject latent trait, or "ability". Unlike other aggregation techniques, this model scores each country and each of the policy instruments under consideration along a continuum. The basic Rasch model was subsequently enriched to allow handling ordinal observations, as in our case, and is generally classified within the framework of Item Response Models. An additional complication in our case is the fact that we have information on each policy instrument for each of the countries under consideration in a longitudinal framework.

To accomodate the structure of our data, we set up a three-level random intercept ordinal logistic model for adjacent categories where policy i (one of the five categories described above) is the first level observation, measurement t (the time period in which responses to each policy are observed) is the second level observation and country j is the third level unit.

In our framework, countries are the observed subjects which are characterised by a score on an ordinal scale for each of the different policy instruments considered (items). According to Bacci & Caviezel (2011) this model can be written as a multilevel Partial Credit Model (PCM) as follows:

$$P(Y_{itj} = m|\theta_{0tj}, \theta_{00j}) = \frac{\exp\left[\sum_{k=0}^{m}(\theta_{0tj} + \theta_{00j} - (\beta_i + \tau_{ik}))\right]}{1 + \sum_{l=1}^{M-1} \exp\left[\sum_{k=0}^{l}(\theta_{0tj} + \theta_{00j} - (\beta_i + \tau_{ik}\Big))\right]} \quad (1)$$

where Y_{itj} is the level of policy i (i = 1, . . . , I) in time t (t = 1,...,T) for country j (j = 1, . . . , n). The parameter β_i, which in the traditional model indicates the average difficulty of the ith item, is now associated with the average difficulty of the ith policy instrument. The parameter τ_{ik} indicates the different threshold in the categories. A threshold is intended as the point in which two adjacent categories have the same probability to be chosen. In PCM the distance between thresholds for an item can differs and moreover the thresholds can differ freely from one item to another (Masters, 1982). More simple Rasch polytomous models exists in which threshold values for all the items are assumed to be equal even if the distance between thresholds can differ (Andrich, 1978). In our context, however, a PCM is more coherent, since the difficulty levels can be assumed to differ between policies and the country should then receive a partial credit (score for each policy) equivalent to the relative level of difficulty of the performance achieved.

The main difference between this formulation and the"traditional" PCM lies in the fact that we account for two levels of clustering of the data, namely time and country, rather than only one. Hence, the presence of two new random effects θ_{0tj} and θ_{00j}, instead of the traditional subject (country) random effect θ_j indicating the level of the latent trait for the jth country. In this framework, the second level residuals θ_{0tj} indicate the deviation of the latent variable θ (i.e. the composite indicator) for year t and country j from the average value of country j: accordingly, they allow for an analysis of time within each country. On the other hand, third-level residuals θ_{00j} indicate the deviation of the latent variable for county j from the average value of the population. θ_{0tj} and θ_{00j} are independent and normally distributed with mean zero and constant variances. They are obtained as the expected a posteriori (empirical) Bayes predictions, namely the posterior distributions of the parameters given the policy responses. In addition, the threshold parameters can be used to characterize the level of complexity/difficulty of the policy portfolio implemented in each year.

The aim of this study is to construct a composite indicator that allows ranking counties over time with respect to their ability to implement environmental and energy policies. We construct a time-varying indicator as a sum of random effects θ_{0tj} and θ_{00j}:

$$CI_{jt} = \theta_{0tj} + \theta_{00j} \tag{2}$$

where CI_{jt} is the time-varying composite indicator of ability to implement environmental and energy policies in country j and time t. The indicator provides continuum of environmental and energy policy ratings and enable to assess and rank countries according to their ability across countries and over time. Standard error of the indicator is derived as follows:

$$SE_{CI_{jt}} = \sqrt{VAR_{\theta_{0tj}} + VAR_{\theta_{00j}}} \tag{3}$$

The outcomes of our statistical framework are thus (1) threshold parameters measuring the intrinsic difficulty/probability of observing a given categorical response for each item/policy instrument; (2) time-country specific intercepts for each country over time and (3) country-specific mean parameters (4) time-specific country indicator which allow for an overall country ranking in each year over the sample period. (2) - (4) are derived conditional on the policy instrument difficulty levels.

However, the ability of each country to implement energy efficiency policy can be thought of as the combination of two different effects. On the one hand, some institutional and economic characteristics are likely to affect each country's ability to pursue efficiency improvements. For example, richer countries might have more room to phase out old capital equipment. Second, conditional on these observable characteristics some countries might be truly more commitment to efficiency than others.

The ranking emerging from a descriptive model like the one described so far does not discriminate between these two different effects. Germany, for example, ranks highest but this could be the result of either better starting conditions or of a true commitment to higher energy efficiency than other countries, or both. To tackle this issue, we combine the multilevel PCM with a latent regression model which allows to explain the variation in the time and country posterior Bayes estimates using a set of covariates. De Boeck & Wilson (2004) refer to this as the *latent regression Rasch model*, namely a *subject explanatory model*, which includes subject properties as explainatory variables for the differences in between-subject scores.

Given our three level structure, we include a vector of covariates $\mathbf{X_j}$ for the third-level residuals θ_{00j} for each country j

$$\theta_{00j} = \mathbf{X_j}\boldsymbol{\zeta} + \varepsilon_{00j} \tag{4}$$

and a vector of covariates $\mathbf{Z_t j}$ for the second level residuals θ_{0tj} for each year t and for each country j

$$\theta_{0tj} = \mathbf{Z_{tj}}\boldsymbol{\gamma} + \varepsilon_{0tj} \tag{5}$$

The new equation of the model is:

$$P(Y_{itj} = m|\theta_{0tj}, \theta_{00j}) = \frac{\exp\left[\sum_{k=0}^{m}(\mathbf{X_j}\boldsymbol{\zeta} + \mathbf{Z_{tj}}\boldsymbol{\gamma} + \varepsilon_{0tj} + \varepsilon_{00j} - (\beta_i + \tau_{ik}))\right]}{1 + \sum_{l=1}^{M-1}\exp\left[\sum_{k=0}^{l}(\mathbf{X_j}\boldsymbol{\zeta} + \mathbf{Z_{tj}}\boldsymbol{\gamma} + \varepsilon_{0tj} + \varepsilon_{00j} - (\beta_i + \tau_{ik}\Big))\right]} \tag{6}$$

The random effects for the second and third level are independent and normally distributed with mean zero and constant variances. They are obtained as the expected a posteriori (empirical) Bayes predictions are the residual components ε_{0tj} and ε_{00j}. These residuals are cleaned from the "comparative advantage" effect due to the effect of clear observables. They can be therefore be interpreted as measures of commitment to efficiency policy. Similarly to the descriptive model, to analyse and rank countries in terms of commitment to efficiency policy over time we build a time-varying indicator for each country as the sum of two residual components ε_{0tj} and ε_{00j}(standard errors are obtained similar to equation 2).

4 Results

4.1 Multilevel Partial Credit Model

The multilevel PCM model with and without latent regression on the subject parameters is estimated using the GLLAMM routine in STATA (Bacci & Caviezel, 2011).

We adjusted original scale of policy variables according to the model requirements. The PCM differs from other statistical models in that it has strict requirement on the data. PCM is valid for measurement only if the data fits the model. In our context, the model requires that a country having a greater ability should have the greater probability of having higher weighted policy value. The model also requires frequently populated response categories and no gap in ordinal response. [6] Original dataset shows many categories with low frequencies. Therefore, we collapse categories into adjacent ones, for those variables with disordered average measures or similar category thresholds. This assures average measures to increase monotonically and a proper separation of thresholds for all the variables. The number of categories varies for each policy instrument and is presented in Table 1. Figure 1 provides an overview of the data by type of instrument and country.

The multilevel PCM results in estimates for each of the parameter thresholds which are reported in Table 2. The assumptions of thresholds differing by policy instrument is confirmed by the empirical findings. The estimated thresholds for the different policy instruments are generally significant, with the exceptions of two thresholds associated with financial instruments. In this case the model suggests that there is big difference between having no financial instrument and implementing at least one or more than three, namely a more complex financial approach.

Conditional on the estimated item thresholds, the variance for the second level (time) and third level (country) residuals (and associated standard errors SE) are estimated at 9.46e-21 (SE: 1.953e-11) and 0.730 (SE: 0.22), respectively. Both effects are significant. Note however that the second level variance,

[6] Categories with low frequencies are problematic because they do not provide enough observations for stable estimation of thresholds. Such infrequently endorsed categories often indicate unnecessary or redundant categories. The same is valid also for variables with category thresholds very close to each other. This suggests that each category corresponds to only a narrow interval in that variable and categories collapsing is recommended Bond & Fox (n.d.).

Difficulty Thresholds	**Coeff.**	**SE**	**p-value**
Regulatory Policy - Threshold 1	0.47	0.22	0.03
Regulatory Policy - Threshold 2	1.87	0.31	0.00
Regulatory Policy - Threshold 3	1.89	0.21	0.00
Voluntary Measures - Threshold 1	0.51	0.23	0.03
Voluntary Measures - Threshold 2	0.71	0.29	0.00
Voluntary Measures - Threshold 3	0.87	0.35	0.01
Voluntary Measures - Threshold 4	0.92	0.28	0.01
Financial Instruments -Threshold 1	-0.73	0.26	0.00
Financial Instruments -Threshold 2	0.35	0.26	0.19
Financial Instruments -Threshold 3	0.57	0.28	0.53
Financial Instruments -Threshold 4	0.84	0.30	0.00
Financial Instruments -Threshold 5	0.90	0.25	0.00
Fiscal/Tax Reductions - Threshold 1	1.29	0.23	0.00
Fiscal/Tax Reductions - Threshold 2	2.43	0.41	0.00
Information/Education - Threshold 1	0.43	0.23	0.07
Information/Education - Threshold 2	0.57	0.27	0.03
Information/Education - Threshold 3	1.10	0.33	0.00
Information/Education -Threshold 4	1.15	0.29	0.00
Energy tax - Threshold 1	0.43	0.23	0.07
Energy tax - Threshold 2	0.57	0.27	0.03
Energy tax - Threshold 3	0.82	0.33	0.00
Energy tax - Threshold 4	0.93	0.23	0.00
Variances and covariances of random effects			
Second Level Variance (Time)	9.46e-21	1.953e-11	0.00
Second Level Variance (Country)	0.73	0.22	0.00

Table 2: Item/policy thresholds

which indicates deviations over time of each country's aggregate score from its own mean, is extremely low in absolute value, while the third level variance, indicating the variation of country scores from the overall mean, is higher in absolute value. Between country variation over our sample period in much higher than within country variation over time.

Given the estimated variance of the second and third level, we can obtain the latent traits as the posterior Bayes estimates from the model.

Figure 2 presents country ranking by derived indicators and confidence intervals for the estimates in the first (2004) and the last (2009) year of the sample period.

The ranking emerging from the multilevel PCM indicates that, conditional on the difficulty of the chosen policy portfolio, Germany, Netherlands and the UK are the proved to be the leaders in terms of energy policy implementation

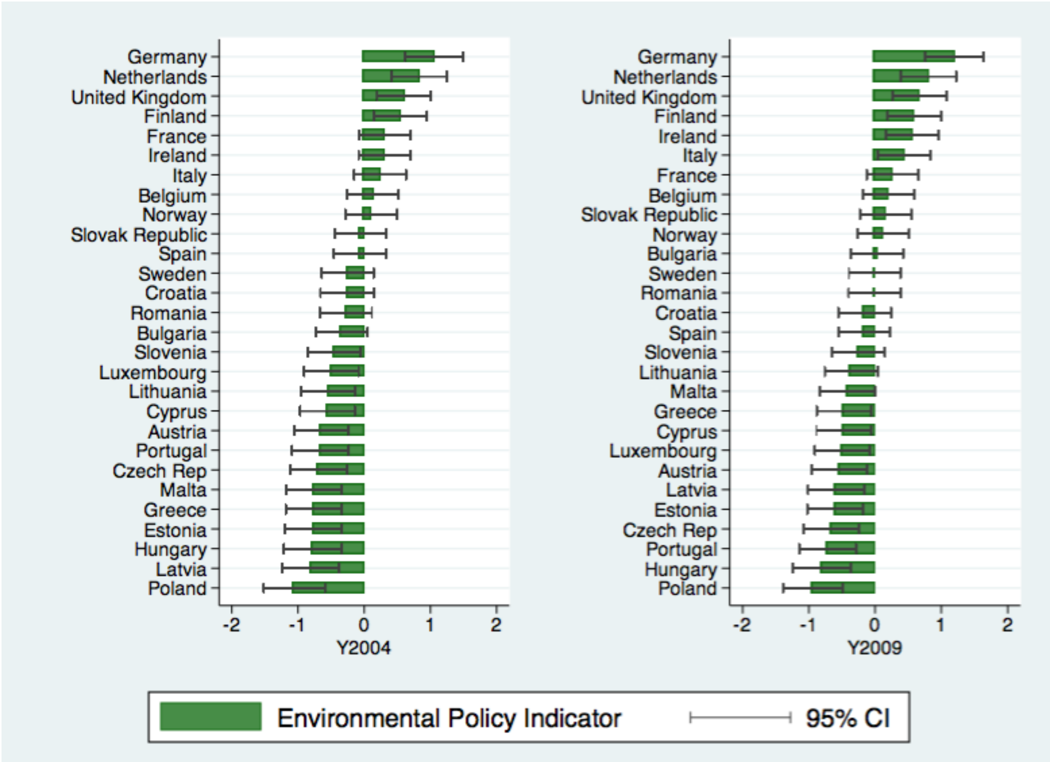

Figure 2: Rank of estimated indicator for multilevel PCM model, years 2004 and 2009

in Europe. At the low end of the rankings are Latvia and Poland. Note that in Figure 2 confidence intervals for the different countries in our sample greatly overlap, indicating that the performance of different EU countries is not strikingly different. Exceptions are countries in the top and the bottom of the ranking, whose confidence intervals does not overlap with that of most of the other countries.

4.2 Explanatory Multilevel Partial Credit Model

In the previous section, we present results on the latent trait and time profile of countries' performances based on a PCM. However, these latent traits (and hence the ranking emerging from Figure 2) are likely affected from the presence of certain observable country characteristics. The fact that Germany, Netherlands and the UK score best in the sample might be the results of a true higher commitment and effort to tackle energy efficiency in these countries, or simply the result of the fact that these countries are among the richest in the sample.

A number of observable characteristics are likely to affect each country's rank in Figure 3. First of all, the likelihood of targeting efficiency in industrial sector will depend on the weight of this sector within each economy. Our expectation in this respect is that the higher the share of GDP accounted for by manufacturing, the higher the commitment to fostering energy efficiency. On one hand, the potential savings from increased energy efficiency would be high. On the other, industry lobbies are likely to pressure governments to establish support measures such as fiscal incentives to lower the costs of energy inputs. Second, countries with higher levels of efficiency might have already reaped the low hanging fruits, and either not feel the need to address the issue of energy efficiency through regulation or find it harder to implement higher costs options. Third, the level of dependence of a given country from energy inputs is also a factor likely to affect its propensity to tackle energy efficiency as a way to achieve energy security. Finally, the availability of energy efficient technologies within any given economy will increase the likelihood that pro-efficiency regulation is passed given that a certain degree of improvement should in theory be easily reached.

We thus extend the model, as explained in the previous Section, to condition each of the estimated latent traits on these observables. Specifically, we select the share of manufacturing in GDP (WDI, 2013), the level of energy efficiency (WDI, 2013), the share of energy imports (WDI, 2013) and the number of energy efficiency patent applications to the EPO by applicants in a given country (OECD, 2013). Descriptive statistics of these variables by country and for the overall sample are displayed in Table 2. All these variables vary greatly between countries, with the exception of the share of manufacturing in GDP, which exhibits low within country variation. For this reason, we include lagged values of energy efficiency, share of energy imports and efficiency patents as time-varying country-level regressors. The share of manufacturing in GDP is instead included as a country-varying regressor to explain third level (between countries) variation.

Country	Energy Efficient Patent Applications to EPO	SD	Energy Intensity	SD	Fuel Imports % of Merchandise Imports	SD	Manufacturing in VA % of GDP	SD
All countries	32.48	82.16	249.1	159.3	13.06	5.187	16.86	4.826
Austria	26.97	12.31	133.9	5.360	11.34	1.502	19.54	0.625
Belgium	19.99	6.795	190.5	8.498	12.80	2.207	16.10	1.193
Bulgaria	0.750	0.664	792.6	97.28	14.90	8.148	15.86	0.756
Croatia	0.125	0.332	241.1	13.80	16.40	2.729	16.63	0.911
Cyprus	2.250	1.003	188.0	9.323	18.20	3.527	8.198	0.700
Czech Republic	2.875	2.663	411.4	41.31	8.520	1.391	24.44	1.103
Denmark	85.92	45.97	96.79	4.428	6.666	1.342	13.79	0.769
Estonia	0.875	0.930	500.7	45.59	14.67	3.872	16.49	1.017
Finland	20.50	11.83	228.4	14.92	15.74	2.943	22.09	2.372
France	89.81	50.77	155.8	5.994	14.20	1.802	12.47	0.951
Germany	385.6	195.4	149.3	7.270	11.47	1.428	22.24	1.517
Greece	3.563	2.636	156.2	6.859	18.72	4.526	9.38	.
Hungary	2	2.187	301.1	11.80	9.087	1.678	22.41	0.460
Ireland	9.625	7.883	93.29	4.149	9.505	2.937	22.97	1.312
Italy	54.75	24.03	126.8	3.847	14.35	3.596	17.96	0.926
Latvia	0.375	0.698	344.1	32.11	14.00	2.101	11.71	1.026
Lithuania	0	0	403.8	58.77	25.20	5.571	19.15	1.622
Luxembourg	5.063	4.608	146.6	10.41	9.402	1.347	7.980	1.394
Malta	0.313	0.557	185.6	11.57	15.25	9.377	15.21	1.213
Netherlands	55.13	25.60	156.9	5.831	14.34	2.635	13.73	0.602
Norway	19.19	10.10	115.9	6.776	5.005	0.878	9.650	0.418
Poland	3.563	3.127	362.5	29.22	10.65	1.060	18.70	0.221
Portugal	3.650	2.694	165.3	7.661	14.05	2.483	14.36	0.729
Romania	0.563	0.585	461.3	59.95	11.80	1.569	29.90	0
Slovak Republic	1.125	0.930	439.4	69.28	12.71	1.061	22.79	1.729
Slovenia	0.750	0.664	241.5	13.56	11.42	1.993	22.63	1.655
Spain	49.74	29.86	149.9	9.161	16.15	3.082	14.97	1.136
Sweden	27.73	13.54	165.5	11.68	12.34	1.567	18.36	1.788
United Kingdom	69.05	24.47	119.8	8.061	9.925	2.497	12.11	0.900

Table 3: Descriptive Statistics

The results on covariates coefficients emerging from the explanatory model are presented in Table 4:

Variable	Coeff.	SE	t
Covariates of Second Level Random Effect (Time)			
Energy Efficient Patent Applications to EPO, (t-1)	0.003	0.001	3.00
Energy Intensity, (t-1)	-0.004	0.001	4.00
Fuel Imports, % of Merchandise Imports (t-1)	0.046	0.012	3.83
Covariates of Third level random effects (Country)			
Manufacturing in Value Added, % of GDP (mean)	0.085	0.033	2.57

Table 4: Results on Second and Third Level Covariates

Conditioning the country-level random effect on these observed covariates, the ranking of countries changes as presented in Figure 3.

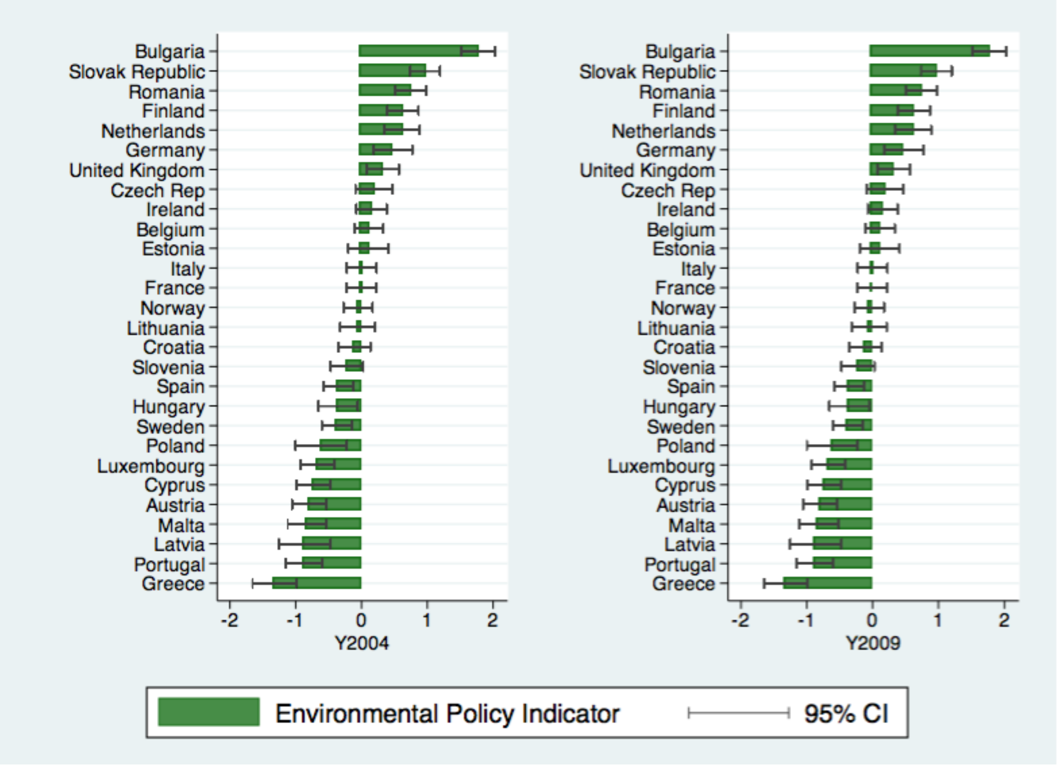

Figure 3: Rank of estimated indicator for PCM explanatory model, years 2004 and 2009

Specifically, controlling for the observable covariates improves the ranking position of those countries which previously scored low due to the fact that the manufacturing sector accounts for a smaller share of the economy, that they are already energy efficient and have reaped the least cost options, whose availability of new efficient technologies is lower and dependence from foreign energy imports is higher. For example, Eastern European countries such as Bulgaria, Slovakia and Romania improve their ranking, because given the inhibiting observable characteristics of their economy, the level of energy efficiency regulatory they put in place is higher than average.

5 Conclusion

This paper presented a novel approach to assessing and comparing countries' energy efficiency or environmental policy portfolios and performance. This method, inspired by the literature on multilevel latent models and Item Response Theory (IRT), results in a ranking of European countries which accounts for the inherent difficulty of a given policy instrument mix. Moreover, the model is extended to deal with the longitudinal data and to adjust the ranking as a result of country-specific economic and institutional observables which are likely to affect the likelihood of regulating energy efficiency.

We believe this approach is a promising one in assessing countries' commitment to environmental and energy policy since it is able to overcome a number of shortcomings of the previous literature on policy indicators. First, while the basic approach we propose has been applied in the statistical literature of scoring, its application to the context of environmental policy is novel. Second, we extend the basic IRT model to a multilevel framework which is consistent with the nature of the policy data available. Third, using the weighted count of policies which are implemented in each country in any given year and effective energy tax rate, our ranking informs about the general commitment of a given country, as well as shed the light on the actual level of stringency of the given policy. Fourth, our approach allows to attribute different weights or difficulty levels to the different policy instruments included in the policy portfolio. Thus, our assessment is conditional on the specific complexity of each country's policy portfolio. Fifth, we combine the multilevel IRT model with a latent regression, thereby allowing each country scores to be conditioned on observed country's characteristics.

We apply this methodology to data on efficiency policy targeting industrial sectors in 27 EU countries in the years 2004-2009. Our results show that accounting for economic and institutional characteristics changes the ranking of countries with respect to energy efficient policy. Specifically, the position of those countries with worse "initial conditions" but which choose to regulate energy efficiency nonetheless, demonstrating a higher than average commitment.

We believe our methodology is a step in the right direction of creating an index of policy commitment and stringency. It applications to other datasets could easily generate similar results. The model presented in this paper can be fruitfully extended to account for the presence of random slopes (as opposed to only random intercepts) and to better study the effect of time. To this end, focusing on a wider sample of countries would be beneficial, since variation in policy responses of the EU member states is necessarily limited given the common framework under which these policies are developed. Our current research is moving in this direction.

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