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Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors

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HIGHLIGHTS

- Weak and strong Porter Hypothesis.
- Panel of manufacturing sectors of 17 European countries between 1997 and 2009.
- Look at overall innovation and productivity impacts.
- Pollution abatement & control expenditures proxy of environmental policy stringency.
- Account for potential endogeneity of *PACE* by adopting instrumental variable approach.

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ABSTRACT

This paper investigates the "weak" and "strong" versions of Porter Hypothesis (PH) focusing on the manufacturing sectors of 17 European countries between 1997 and 2009. The hypothesis that well-crafted and well-enforced regulation would benefit both the environment and the firm was originally proposed by Porter (1991) and Porter and van der Linde (1995). To date, the literature has analyzed the impact of environmental regulation on innovation and on productivity mostly in separate analyses and focusing on the USA. The few existing contributions on Europe study the effect of environmental regulation either on green innovation or on performance indicators such as exports. We instead look at overall innovation and productivity impacts. First, focusing on overall innovative activity allows us to account for potential opportunity costs of induced innovations. Second, productivity impacts are arguably the most relevant indicators for the "strong" PH. As a proxy of environmental policy stringency we use pollution abatement and control expenditures (*PACE*), one of the few sectoral level indicators available. We remedy upon its main drawback, namely potential endogeneity, 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 "weak" PH. This result is in line with most of the literature. On the other front, we find no evidence in favor of the "strong" PH, 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 European manufacturing sectors. The standard 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* investments necessary to modify production activities. On the other hand, firms' budgets are limited due to financial constraints. By committing resources to comply with environmental regulation, firms also incur indirect (opportunity) costs because they cannot invest in other profitable opportunities.

Porter (1991) and Porter and van der Linde (1995) challenged this view. They argued that well-crafted and well-enforced regulation would benefit both the environment and the firm. The

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proposition, known as Porter Hypothesis (PH), was initially formulated in rather general terms. Firms face market imperfections, such as asymmetric information, organizational inertia or control problems (Ambec et al., 2013). Environmental regulation would push firms to overcome some of these market failures and to pursue otherwise neglected investment opportunities. The key mechanism in this respect is that regulation promotes innovation aimed at lowering the cost of compliance, which would in turn increase resource efficiency and product value, offset compliance costs and enhance firms' productivity. Environmental regulation is thus advertised as a "win-win" strategy, leading to better environmental quality and higher firms' productivity.[1]

Given the important implications for policy making and firms performance, proving or disproving the PH has been the focus of many empirical contributions since the early 1990s. Three distinct research statements have been identified (Jaffe and Palmer, 1997). First, the "narrow" 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" PH affirms the positive effect of well-crafted environmental regulations on environmental innovation (even when such 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 firms' competitiveness and productivity.

Given the recent energy and environmental policy developments, testing the link between environmental regulation and competitiveness is particularly relevant for Europe. 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. But empirical evidence in this respect is scant for Europe, as most studies focus on the US.

This paper investigates the PH using cross-country sector-level data for 17 European countries between 1997 and 2009. Our analysis contributes to the literature in several ways. First, unlike several other studies, we look at both the weak and at the strong PH, focusing on both innovation and productivity. Second, unlike country-level analyses, our sector-level approach captures the effects of sector-specific environmental policies, and the dynamics of sectoral competition. Third, we use pollution abatement and control expenditures (*PACE* henceforth) as our environmental policy indicator. *PACE* include the flow of industry investment and current expenditures directly aimed at pollution abatement and control. Hence, they provide information on the response of each sector to the pressure of environmental policy. It is thus arguably a good candidate to measure the different impact of environmental policy on manufacturing sector sexpecially due to its sectoral variability, certainly a plus in our context. Moreover, *PACE* data were used in the seminal paper by Jaffe and Palmer (1997) for US sectors: we implement their approach when assessing European industries' innovation activity. Finally, we recognize the potential endogeneity of *PACE* and address it using an instrumental variable approach. Only a handful of papers have tackled this important issue: if overlooked it may lead to biased estimates.

The paper proceeds as follows. Section 2 summarizes the literature on the PH. Section 3 describes the competitiveness indicators and the environmental regulation proxy and presents descriptive statistics. The empirical results are presented in Section 4. Section 5 discusses the policy implications of our findings. Section 6 describes the conclusion.

2. Related literature

The empirical literature investigating the PH is vast, but largely focused on the US (Ambec et al., 2013). Two main groups of studies can be identified. Those testing the weak PH focus on the relationship between environmental regulation and innovation. Those testing the strong PH focus instead on the relationship between environmental regulation and proxies of competitiveness.

The first paper to look at the weak PH is the descriptive analysis of Lanjouw and Mody (1996) for the US, Japan and Germany. Subsequent formal tests present mixed results. Jaffe and Palmer (1997) find a positive link between regulation (proxied by *PACE*) and *R&D* expenditures in US manufacturing sectors, but not between regulation and patent applications. Studies focusing on environmental innovation reach instead a different conclusion. Brunnermeier and Cohen (2003), Popp (2003, 2006), De Vries and Withagen (2005), Carrion-Flores and Innes (2010), Johnstone et al. (2010), Lanoie et al. (2011), Lee et al. (2011), Kneller and Manderson (2012) find a positive relationship between green patents and environmental regulation.

The evidence is more mixed for the strong PH (Jaffe et al., 1995; Koźluk and Zipperer, 2013). Early studies on the US concluded that environmental regulation caused a productivity slowdown, presumably due to a displacement of "productive" investment by environmental regulation (Gollop and Roberts, 1983; Gray and Shadbegian, 1993, 2003). More recently, Berman and Bui (2001) and Alpay et al. (2002) find positive results. However, in Greenstone et al. (2012) stricter air quality regulations are associated with a roughly 2.6 percent decline in the *TFP* of US manufacturing plants and Lanoie et al. (2008) show a negative impact of contemporaneous environmental regulation on *TFP* growth for Québec, but a negative lagged effect. Costantini and Crespi (2008) and Costantini and Mazzanti (2012) focus on Europe and the export effects of several environmental policy indicators. Environmental policies do not seem to harm export competitiveness of manufacturing sectors, whereas specific energy tax policies and innovation efforts positively influence export flows dynamics. Using firm-level German data, Rennings and Rammer (2010) find that environmental innovations on average do not perform worse compared to other innovations in terms of profitability impact, while Rexhäuser and Rammer (2014) conclude that the strong version of PH does not hold in general, rather the impact of regulation on competitiveness is heterogeneous depending on the type of environmental innovation.

Only a handful of papers test both versions of the PH. Hamamoto (2006) and Yang et al. (2012) investigate both innovation and productivity responses to environmental regulation, proxied by *PACE*, in Japan and Taiwan respectively. Lanoie et al. (2011) find a positive and significant link between perceived stringency of environmental regulations and environmental innovation, consistent with the weak PH, using company survey data in 7 OECD countries. Furthermore, the "predicted" environmental innovation from the weak PH equation has a positive and significant impact on business performance, providing evidence in support of the strong PH. van Leeuwen and Mohnen (2013) use a structural approach and a comprehensive panel of Dutch firm-level data to corroborate the weak, but not the strong, PH. Finally, Franco and Marin (2013) look at innovation and at *TFP* using energy tax intensity to proxy environmental policy stringency in manufacturing sectors in

[1] An example is distillers of coal tar in the US. In 1991 many of these firms opposed the regulations requiring substantial reductions in benzene emissions because at the time it was thought that the only means to achieve this goal was to cover the tar storage tanks with costly gas blankets. However, the regulation prompted Aristech Chemical Corporation to develop a method of removing benzene from tar in the first processing stage, eliminating the need for gas blankets and saving $ 3.3 million (see Zaelke et al., 2005).

7 European countries. Stringency is the most relevant driver for innovation and most of its effect on productivity is direct. Conversely, the effect of induced innovation is not statistically significant.

There are aspects to note concerning these EU-based studies. First, most are country-level analyses and as such they do not account for heterogeneity in sectoral responses to regulation. In this paper we overcome this shortcoming using sectoral level *PACE* data, which have not been previously exploited.

Second, most studies test the weak PH. They focus on how environmental innovation responds to regulation, but do not test the effect of stringent environmental regulation on total manufacturing innovation. This is insufficient, 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. We look at overall innovation, in terms of either *R&D* expenditures or patent applications. Our approach overlooks issues of crowding out between green and non-green innovation, but we make this choice for three main reasons: first, there is little or no evidence of the overall innovation effect of environmental policy. Second, it is important to account for the opportunity costs of green innovation, and test whether overall innovation are affected by policy. Finally, isolating green innovation at the sectoral level in a cross country setting is neither straightforward nor completely safe, since it relies on strong assumptions.

Third, European studies focusing on the strong PH use data on exports or profitability to measure competitiveness and do not test how productivity responds to stringent environmental policy. In this paper we consider total factor productivity, either levels or growth, as basis for testing the allegedly most controversial version of the PH.

Finally, only very few papers in this area recognize the potential endogeneity of *PACE*. Exceptions are de Vries and Withagen (2005), Carrion-Flores and Innes (2010), and Kneller and Manderson (2012). Not accounting for the endogeneity of environmental policy proxies may bias estimates of environmental regulation effects on economic performance. In this paper the endogeneity of our policy indicator *PACE* is accounted for and appropriately dealt with.

3. Data and methods

Our empirical investigation of the PH is based on the following expression:

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

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

3.1. Competitiveness indicators

Competitiveness C is represented by technological innovation TI in the weak PH and by factor productivity FP in the strong PH. TI is proxied by either *R&D* expenditures or patent statistics, as in Jaffe and Palmer (1997). Both indicators have been widely used in the innovation literature (Griliches, 1990). *R&D* expenditures represent an input of the knowledge production function and measure the effort of private firms in pursuing innovation. Industrial *R&D* expenditures in millions of Euro at 2005 prices are taken from the ANBERD database (OECD, 2012). We complement this with data from EUROSTAT (2012a) for some countries like Bulgaria, Sweden, Slovakia and the UK. The data are available for the period 1998–2009. Conversely, patent statistics approximate the output of the knowledge production function. We use applications to the EPO from EUROSTAT (2012b) which assigns patent applications according to the inventor country of residence and uses fractional counting.[2]

To assess the impact of environmental regulation on productivity FP, we use Total Factor Productivity (TFP) to proxy for sectoral economic performance (Gray and Shadbegian, 1993, 2003). TFP indicates how productively inputs are combined to generate gross output. Conceptually, TFP captures technical change, but in practice it also reflects also efficiency change, economies of scale, variations in capacity utilization and measurement errors. We compute TFP using data from the EU KLEMS (2009).[3] Following the literature on the strong PH, we estimate productivity equations both in levels and in growth rates, as there is no a priori guide as to which proxy to use.

3.2. Environmental policy indicators

To proxy for environmental regulation we use data on Pollution Abatement and Control Expenditures (*PACE*). Recently, there has been a surge of interest in measures of environmental policy stringency. A few alternatives have been proposed (Brunel and Levinson, 2013; Galeotti et al., 2014; Nesta et al., 2014): all of them are characterized by pros and cons both from a conceptual and a practical perspective (Brunel and Levinson, 2013). This notwithstanding, the *PACE* indicator has not been previously used in the context of sector-level studies of the PH in Europe and is particularly well suited because it captures 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 expenditures directly aimed at pollution abatement and control. *PACE* data for the EU manufacturing sectors are available for the period 1997–2009 from EUROSTAT (2012c) and fill missing observations with comparable data from various National Statistics Offices.[4]

3.3. Descriptive statistics

The sample has been selected based on data availability of our environmental regulation indicator. and 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. The level of aggregation by industrial sectors varies across the five different data sources we used (EUROSTAT, EU KLEMS, WIOD, OECD STAN and OECD ANBERD). We therefore base our analysis on the sectoral classification of the *PACE* variable, which includes nine macrosectors. The classification and the reference to

[2] Patent indicators suffer from the major drawback of greatly differing in quality and in the magnitude of inventive output (Griliches, 1990). We mitigate this concern by using EPO applications which are more expensive than national applications. This difference in cost provides a quality threshold (OECD, 2009). Since patents are assigned using fractional counting, there is no need to resort to count data models in the estimation.

[3] Details on the construction of our *TFP* proxies are provided in Rubashkina et al. (2014).

[4] *PACE* are in million Euros and constant prices. Sufficiently complete *PACE* data can be gathered for 17 European countries. However, also for these countries there are gaps. For a detailed description of the contents of *PACE* see Rubashkina et al. (2014).

the two-digit European NACE revision 1.1 sectoral classification are shown in Table A.1.[5]

Table A.3 shows striking differences in our competitiveness indicators between new and old Member States. In particular, Finland, Netherlands, Norway, and the UK have patent and/or *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 virtually zero in Portugal. On average *PACE,* are equal to 3.6% of value added or 0.9% of gross output. Finland, Portugal, Norway, Spain and the UK are behind the other countries in terms of share of environmental expenditures in *VA* (between 2% and 3%). New Member States have larger environmental expenditures intensities than old Member States, presumably due to the fact that the former needed to catch up with EU requirements in a relatively short period of time. Among the old Member States, Sweden and the Netherlands have the highest expenditures intensities.

Focusing on the sectoral breakdown, some sectors, such as 5 ("Coke, refined petroleum products and nuclear fuel"), 6 ("Chemicals; rubber and plastic products") and 9 ("Machinery and equipment"), have higher-than-average patent and *R&D* intensities (Table A.4). The former ranges between 19 and 36 patents per billion of Euro against an average value of 13 patents per billion of Euro, while the latter is 4.9–8.2% versus an average of 2.9%. The highest levels of *TFP* are in sectors 6 ("Chemicals; rubber and plastic products"), 7 ("Other non-metallic mineral products") and 8 ("Basic metals"). With respect to *PACE*, we observe sizeable differences between sectors 5 ("Coke, refined petroleum products and nuclear fuel"), 6 ("Chemicals; rubber and plastic products") and 8 ("Basic metals") and the rest of the sample. These sectors spend more on pollution abatement and control activities than average: their shares of *PACE* in *VA* are 9.5%, 4.0% and 6.1%, respectively, against an average of 3.6%. These three sectors are in fact characterized by high energy intensity.[6] Therefore, energy intensive sectors appear to spend more on environmental expenditures regardless of environmental regulation stringency.

4. Empirical results

We begin our empirical analysis by studying the relationship between environmental regulation and innovative activity.

4.1. Environmental regulation and innovation activity: the weak Porter Hypothesis

The log–log specification relating innovation to environmental policy, similar to the one originally used in the paper of Jaffe and Palmer (1997) and adapted to a multi-country analysis, is

$$\ln TI_{ijt} = \beta \ln ER_{ijt-q} + \gamma \ln Z^{TI}_{ijt-1} + \alpha_{ij} + \mu_t + \varepsilon_{ijt} \tag{2}$$

where TI_{ijt} is either total *R&D* expenditures (*R&D*) or total patent applications (*PAT*) in country *i*, sector *j*, and time *t*, and environmental regulation (*ER*) is represented by *PACE* expenditures.[7] Eq. (2) controls for both observed and unobserved sector-country specific heterogeneity. To deal with the former we include a vector of sector- and country-level covariates (Z^{TI}). Firstly, we include sectoral value added (*VA*) as a scaling variable, since 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. Secondly, a prominent role is played by technology push factors (Schumpeter, 1943; Schmookler, 1966; Horbach et al., 2012). We hence add a knowledge stock variable (*KR&D* or *KPAT*) capturing previous innovation experience, which is expected to have a positive influence on the innovation capacity because innovators can "stand on the shoulders of the giants" (Caballero and Jaffe, 1993). Industries which exhibit greater past investment in technological development are also more likely to engage in future innovative practices (Baumol, 2002). The stock of knowledge is calculated using the perpetual inventory method and a 10% depreciation rate (Keller, 2002). Thirdly, we include import penetration (*IMP*) to proxy for external competition and export intensity (*EXP*) which controls for a sector's participation in foreign trade. Schumpeter (1943) postulated a positive influence of market concentration on innovation, since market concentration reduces uncertainty and motivates firms to invest in *R&D*.[8] Moreover, 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). Finally, 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). The data for sector level import intensities (ratio of imports over the sum of domestic production and imports) and export intensity (ratio of exports over domestic production) are taken from WIOD (2012). To control for the effect of sectors' structural change due to creation, death or the relocation of enterprises on innovation intensity we include enterprises birth (*BR*) and death (*DR*) rates in the equations. The former is the number of new enterprises over total enterprises, the latter is the number of death enterprises over total enterprises.[9] The data are from EUROSTAT (2012a). Finally, the share of *R&D* appropriations in total government expenditures from GBAORD (OECD, 2012) accounts for the impact of public support to private *R&D*. These are country level aggregates with no sectoral detail.

The control variables in Z^{TI} (with the exception of $R\&D^{GOV}$) are lagged once to avoid simultaneity problems with innovation activity, an issue to which we return in the next section. Finally, Eq. (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*.[10] Since in our context unobservable factors, that are constant over time but vary across countries and sectors, can affect innovation activity and are likely to be correlated with the other regressors, we estimate the innovations models using a fixed effects (FE) estimator.[11]

[5] Definition, data sources and period of availability of all the main variables used in the present investigation are reported in Rubashkina et al. (2014), as are the description of outliers which were excluded from the analysis.

[6] Energy intensity is defined as emission-relevant energy use (in TOE) over *VA* from WIOD (2012). There are minor differences in the energy intensity classification comparing to the innovation indicators and *PACE*. Due to minor differences between the sectoral classification of *PACE* and WIOD "Fabricated metal" is included in the sector 8, rather than in the sector 9.

[7] Alternatively we could regress the ratio *R&D/VA* or *PAT/VA* on the ratio *PACE/VA*. However, a measurement error in value added could cause Eq. (2) to exhibit

(*footnote continued*)
spurious correlation. Nevertheless, we estimated the equation in ratio form as a robustness check. The results for *PACE* were very similar to those presented here and are available upon request.

[8] Some 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 a priori ambiguous.

[9] Birth and death rates are highly correlated. Results including either DR or BR alone do not differ from those presented below and are available from the authors.

[10] We also assume that shocks in innovations could vary between new and old member states and therefore we allow for time effects μ_t and their interaction with an "Old Member countries" dummy variable, denoted by *OLD*.

[11] This choice was validated with a Hausman test.

Table 1
Weak PH – *R&D* and patents FE regression results.

	R&D				Patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PACE	0.043 (0.039)	0.033 (0.041)	–	–				
PACE(−1)	–	–	−0.021 (0.042)	−0.045 (0.044)	0.086*** (0.019)	0.030** (0.021)	–	–
PACE(−2)					–	–	0.096*** (0.029)	0.002 (0.020)
VA(−1)	0.042 (0.042)	0.013 (0.061)	0.084 (0.078)	0.031 (0.129)	0.061 (0.048)	−0.045 (0.029)	−0.032 (0.041)	−0.045 (0.033)
GOVR&D(−1)	0.043 (0.183)	0.311** (0.141)	−0.076 (0.189)	0.132 (0.167)	0.323*** (0.104)	−0.073 (0.069)	0.286*** (0.111)	−0.086 (0.082)
KR&D(−1)	–	0.654*** (0.209)	–	0.633*** (0.189)				
KPAT(−1)					–	0.509*** (0.082)	–	0.487*** (0.091)
EXP(−1)	–	0.434* (0.222)	–	0.519*** (0.178)	–	0.05 (0.067)	–	0.105 (0.093)
IMP(−1)	–	−0.32 (0.218)	–	−0.633* (0.348)	–	−0.277** (0.112)	–	−0.385*** (0.151)
DR(−1)	–	1.806** (0.789)	–	1.938*** (0.678)	–	0.024 (0.212)	–	0.129 (0.261)
BR(−1)	–	−1.064 (0.821)	–	−0.898 (0.704)	–	0.275* (0.161)	–	0.483* (0.289)
F-test	1.32*	5.61***	1.45**	8.46***	6.89***	6.40***	10.32***	6.70***
Within R^2	0.05	0.22	0.05	0.26	0.37	0.39	0.39	0.35
No. of observations	750	515	694	512	913	639	883	587
No. of country-sector effects	129	105	129	104	153	125	151	126

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

4.1.1. Estimation results

The main difference between the *R&D* and *PAT* regressions lies in the lag structure incorporated in the our models to test the dynamic effect of environmental regulation on innovation. We assume that firms immediately react to the introduction of regulation and engage into *R&D*. However, it may take time to mobilize the resources necessary for *R&D* investments. Therefore, in the *R&D* equation we test for contemporaneous, one and two year lagged effects of environmental policy. Previous findings show that the policy variable is most significant with lags between zero and two years (Brunnermeier and Cohen, 2003; Hamamoto, 2006; Johnstone et al., 2010). As for patent data, we assume that the whole innovation process from *R&D* investment to a patent application takes time and that environmental policy-induced innovations are translated into patents with at least one (or more) year lag period. Thus, we include from one to three-year lagged regulation variables in the patent equation.

Table 1 reports the estimation results of the effect of environmental regulation on *R&D* efforts and patenting activity respectively.[12] Columns 1–2 (resp. 5–6) and columns 3–4 (resp. 7–-8) differ for the timing of the impact of *PACE* on the innovation variables. As a starting point, columns 1 and 3, and columns 5 and 7, report the results 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, enterprises' birth and death rates in the remaining columns.

The first and most relevant result is that in no case is the impact of environmental regulation on *R&D* efforts statistically significant across all the specifications. On the contrary, the effect of *PACE* on patent applications is always positive and significant. Here a 10% increase in *PACE* is associated with a 0.3–0.9% increase in patent applications.[13] Hence, environmental regulation does not seem to have an effect on overall *R&D*, but it increases the number of patents in the short and in the medium run. While these findings are in line with the literature pointing to a positive and significant impact of environmental regulation on innovation (Ambec et al., 2013), they are in contrast with those of Jaffe and Palmer (1997), who found a positive effect of *PACE* on *R&D* but not on patents. Our explanation to reconcile this difference is that in the EU more stringent regulation does not seem to provide enough stimulus to one important input to the production of knowledge, but it does favor a more efficient combination of all the inputs involved which results in a higher knowledge output, as proxied by patents.

The coefficients associated with other controls used in the regressions are generally in line with expectations. For instance, the positive coefficients associated with the knowledge stocks confirm the results from a rich literature pointing to the "standing on the shoulder of the giants" effect. Participation in international trade has a positive effect on sectoral *R&D*, confirming positive learning-by-exporting effects. External competition, measured by import intensity, has a negative and significant impact both on *R&D* and patents, 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, while patent intensity is positively affected by opening of new enterprises.

[12] Due to data availability, the estimation of the *R&D* equations are carried out on a smaller sample (1999–2009) than that of the patent equations (1997–2009). For details se Rubashkina et al. (2014).

[13] Various additional robustness are available from the authors upon request. For instance, the results of Table 1 do not change if we considered longer lags for *PACE*.

In several specifications the public support of private *R&D*, as measured by the share of public *R&D* in government budget, has a positive effect on private *R&D* and patent behavior.

4.1.2. Endogeneity of PACE

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. The endogeneity of *PACE* could cause either a downward or ad upward bias in the estimation of its effect. For instance, the assumption that omitted common determinants of the cost of regulation (*PACE*) and of innovation are time-invariant could be too strong, as these factors are likely to change over time. If this assumption is relaxed, we cannot hope to capture these factors simply including country-sector fixed effects. Moreover, *PACE* estimates could be biased due to measurement error problems. *PACE* are self-reported by firms that could face difficulties in identifying the portion of the expenditures associated with regulatory compliance in their total expenditures. It could therefore be reported with errors. Finally, *PACE* is not adjusted to take into account transfers or subsidies. Yet, some Member Countries use subsidies and refund schemes to protect producers from any negative effect on competitiveness arising from increases in input costs.[14]

To overcome potential endogeneity issues we adopt an instrumental variable (IV) estimation approach. Although finding suitable instruments is not easy, *PACE* is instrumented here with the average share of *PACE* intensity for eight adjacent sectors of the same country excluding the current sector ($PACE/VA_{-j}$). In fact, there is a strong correlation between environmental policies applied to different sectors within one country: adjacent sectors' *PACE* intensity is therefore strongly correlated with a sector's *PACE* intensity within a country, while it should have no direct effect on the sectors' innovative activity or productivity. We also interact this instrument with pre-sample (year 1996) sectoral energy-intensity ($PACE/VA_{-j} \times EI_{pre}$), as regimes of environmental regulation of energy-intensive sectors could differ from those of less energy-intensive sectors within the same country: thus environmental policies of energy intensive sectors could stand out from policies of adjacent sectors.[15] The identification assumption for all the instruments is that, conditional on sectoral value added, innovation stock, government *R&D* support, import and export intensities, enterprises demographic indicators, country-sector fixed effects and time effects, these instruments are strong predictors of sector-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 identified and the over identified equations, respectively. The first stage attempts to isolate the portion of variation in *PACE* intensity that is attributable to exogenous environmental expenditures. Using the predicted *PACE* from this stage we can be relatively confident that our results truly reflect causal effects of environmental costs on sectoral innovation performance. Moreover, 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 2 and 3 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 *PACE*. The coefficient of $PACE/VA_{-j}$ and its interaction with the pre-sample *EI* are shown to be 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 shows a *F*-statistic that exceeds a widely used rule of thumb of 10 (Staiger and Stock, 1997) in columns 5–8 of Table 2 and in columns 1–4 of Table 3, although in the other cases it is close to that value. On this basis the joint significance of excluded restrictions in the first-stage regressions is not rejected. Moreover, *F*-statistic 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 we report is Shea (1997)'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 weak instrument-robust Anderson and Rubin (1950) 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 over-identifying restrictions are valid. Finally, the *C*-test rejects the null hypothesis that 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. The validity of the instruments are tested with Hansen's *J*-test. As the reported *p*-values are above 0.05 in all the models, we do not reject the joint null hypothesis that the instruments are valid, i.e. they are uncorrelated with the error term, and conclude that the over-identifying restriction is valid.

Tables 4 and 5 respectively report the second-stage estimation results of the *R&D* and *PAT* equations controlling for the potential endogeneity of *PACE*. Columns 1–4 and 5–8 correspond to the specifications with current and one-year lagged *PACE* (Table 2), and with one-year and two-year lagged *PACE* (Table 3). In all specifications of the *R&D* equation (Table 4) instrumented *PACE* is insignificant, in keeping with the results of the FE estimation shown in Table 1. The exception is the last two columns, where *PACE* is lagged and all covariates are included, in which case it is negative and statistically significant. Results available from the authors show that environmental regulation proxied by *PACE* does not affect *R&D* after one-year period.

In the patent equation one-year lagged *PACE* remains positive and strongly significant with a coefficient of similar magnitude to that of the FE estimation. Other things equal, an additional 10% of regulation compliance expenditures increases the number of patent applications by approximately 0.1% in the one-year period. The same holds for the two-year lagged effect of environmental regulation on patents, if we look at the first two columns. Other things equal, an additional 10% of regulation compliance expenditures decrease the number of patent applications by 0.2%. The exception is given by the negative statistically significant impact of lagged *PACE* of the last two columns. With the exception of public *R&D* the effects of the other control variables are robust to the change from the FE to IV estimations in both the *R&D* and the patent equations.

Taking together the results of *R&D* and patent equations, we conclude that environmental regulation leads to an increase in patent applications. The IV results of both innovation equations highlight the upward bias of the lagged *PACE* coefficients in the FE estimation.

[14] If we go back to Eq. (1) and assume that *ER* is not observed, we can specify the following: (I) $C=f(ER,Z)$ (II) $PACE=g(ER,W)$; we can solve (ii) for *ER* as a function of *PACE* and substitute the result in (i) so that: (III) $C=h(PACE,W,Z)$ which is the baseline equation we estimate. This clarifies the endogeneity of *PACE*.

[15] We should note that when using $PACE/VA_{-j}$ as well as $PACE/VA_{-j} \times EI_{pre}$ we lose several observations.

Table 2
Weak PH – *R&D* IV regression – first stage results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PACE/VA_{-j}$	0.268***	0.350***	0.204***	0.268***	–	–	–	–
	(0.056)	(0.071)	(0.072)	(0.073)				
$PACE/VA_{-j}(-1)$	–	–	–	–	0.395***	0.414***	0.374***	0.360***
					(0.089)	(0.092)	(0.101)	(0.009)
$PACE/VA_{-j} \times EI_{pre}$	–	−0.074**	–	−0.244**	–	–	–	–
		(0.042)		(0.111)				
$PACE/VA_{-j} \times EI_{pre}(-1)$	–	–	–	–	–	−0.122*	–	−0.334**
						(0.071)		(0.148)
$VA(-1)$	0.105**	0.176*	0.089**	0.171*	0.106	0.119	0.112	0.103
	(0.048)	(0.101)	(0.041)	(0.089)	(0.084)	(0.092)	(0.083)	(0.091)
$GOVR\&D(-1)$	−0.325*	−0.354**	−0.281	−0.294	−0.356*	−0.351*	−0.387*	−0.371
	(0.167)	(0.174)	(0.195)	(0.204)	(0.201)	(0.201)	(0.230)	(0.231)
$KR\&D(-1)$	–	–	0.244*	0.226	–	–	0.171	0.217
			(0.141)	(0.149)			(0.178)	(0.181)
$EXP(-1)$	–	–	0.025	−0.01	–	–	−0.118	−0.107
			(0.158)	(0.182)			(0.174)	(0.180)
$IMP(-1)$	–	–	−0.068	−0.207	–	–	−0.298	−0.24
			(0.266)	(0.278)			(0.341)	(0.343)
$DR(-1)$	–	–	−0.286	−0.45	–	–	2.392***	2.448***
			(0.532)	(0.509)			(0.878)	(0.861)
$BR(-1)$	–	–	−0.291	0.036	–	–	1.536*	1.584*
			(0.661)	(0.662)			(0.892)	(0.891)
F-statistics	5.65	8.319	4.95***	7.73***	12.985	12.687	14.08***	14.53***
Within R^2	0.166	0.205	0.08	0.09	0.181	0.198	0.14	0.15
C-test of endogeneity (*p* value)	0.1	0.53	0.089	0.486	0.4	0.13	0.019	0
Weak-ID test (*F* instruments)	17.73	15.35	9.17	12.94	20.48	13	13.48	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
Partial R^2	0.05	0.08	0.03	0.06	0.08	0.1	0.07	0.09
AR Weak-ID-robust *F* (*p* value)	0.21	0.74	0.1	0.22	0.45	0.47	0.01	0
AR Weak-ID-robust χ^2 (*p* value)	0.2	0.74	0.09	0.2	0.44	0.45	0.01	0
J-statistics (*p* value)		0.33		0.25		0.5		0.27
No. of observations	693	629	498	480	654	620	509	492
No. of country-sector effects	127	120	108	102	124	117	104	98

4.2. Environmental regulation and productivity: the strong Porter Hypothesis

We now examine the relationship between regulation stringency and productivity. Productivity may be affected by environmental regulation through a number of channels. First, the firm may need to use additional inputs, such as labor, materials or capital to comply with environmental requirements (the direct effect). Consequently, an increase in production costs could result in a negative impact on productivity in the short run. Second, environmental regulation would affect the stock of knowledge which in turn could positively impact productivity (the indirect effect). The latter effect is likely to appear in the medium-long run.

In view of the multiple channels through which environmental regulation may affect productivity, we model the link between the former and the latter through reduced-form equations. In such a setup, a positive coefficient of the environmental regulation variable means that an induced innovation effect outweighs the additional input costs due to regulation, resulting in enhanced productivity.

The specification we use is

$$\ln FP_{ijt} = \beta \ln ER_{ijt-q} + \gamma \ln Z^{FP}_{ijt-1} + \alpha_{ij} + \mu_t + \varepsilon_{ijt} \quad (3)$$

where FP_{ijt} is factor productivity in country *i*, sector *j*, and time *t*, environmental regulation (*ER*) is given by *PACE* and Z^{FP} is a vector of sector- and country-level covariates. Our first proxy of productivity is the level of *TFP*.

To control for factors that could affect sectoral productivity we include a vector of controls including value added, import penetration, export intensity, enterprises birth and death rates. First, as larger industries are likely to have greater absolute levels of *PACE*, we include value added as a scaling factor. Next, we include import intensity as the role of import penetration is stressed in the cross-country productivity growth literature (Griffith et al., 2004). Export intensity is added to control for a sector's participation in foreign trade. As suggested by the learning-by-exporting hypothesis, strong competition abroad could encourage productivity improvements (Grossman and Helpman, 1991). Finally, we control for the effect of a sector's structural change due to enterprises creation, death or relocation by incorporating enterprises birth and death rates in the equation. The productivity impact of environmental regulation is conditional on plants survival. Stringent regulation can result in the closure of some plants. Not accounting for survivorship the true productivity effect could be understated. Finally, as before, the above covariates are lagged one year to avoid two-way causation with productivity.[16]

An alternative version of (3) that we consider proxies *FP* with total factor productivity growth (*TFPG*), as there is no a priori reason to prefer, in the present context, levels or growth of TFP. In the *TFPG* specification, in keeping with a large literature, we adopt a catch-up specification and supplement the vector Z^{FP} with a measure of *TFPG* at the technological frontier (*TFPG-frontier*) and a measure of the distance from that frontier (*TFP-gap*): both are found to be important

[16] 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 a boost of production, thus the causality between productivity and *VA* could also be bidirectional.

Table 3
Weak PH – patents IV regression – first stage results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PACE/VA_{-j}(-1)$	0.413***	0.458***	0.689***	0.673***	–	–	–	–
	(0.071)	(0.070)	(0.067)	(0.061)				
$PACE/VA_{-j}(-2)$	–	–	–	–	0.443***	0.448***	0.575***	0.486***
					(0.071)	(0.070)	(0.078)	(0.081)
$PACE/VA_{-j} \times EI_{pre}(-1)$	–	0.093***	–	−0.166*	–	–	–	–
		(0.03)		(0.10)				
$PACE/VA_{-j} \times EI_{pre}(-2)$	–	–	–	–	–	−0.128**	–	0.547***
						(0.056)		(0.156)
$VA(-1)$	0.171**	0.189**	0.180*	0.176*	0.093	0.106	0.404***	0.439***
	(0.091)	(0.090)	(0.091)	(0.104)	(0.056)	(0.072)	(0.141)	(0.130)
$GOVR\&D(-1)$	−0.186	−0.198	−0.292	−0.277	−0.105	−0.091	−0.198	−0.221
	(0.156)	(0.172)	(0.211)	(0.221)	(0.178)	(0.180)	(0.190)	(0.181)
$KPAT(-1)$			0.378**	0.390**			0.406*	0.415*
			(0.182)	(0.180)			(0.224)	(0.224)
$EXP(-1)$			0.467***	−0.468**			−0.351*	−0.289
			(0.178)	(0.181)			(0.211)	(0.212)
$IMP(-1)$			0.486	0.491			0.888**	0.847**
			(0.301)	(0.311)			(0.381)	(0.351)
$DR(-1)$			−0.637	−0.646			−0.765*	−0.901**
			(0.490)	(0.501)			(0.450)	(0.421)
$BR(-1)$			0.427	0.467			−0.062	0.204
			(0.432)	(0.423)			(0.478)	(0.402)
F-statistics	16.27	16.646	10.76***	11.00***	7.662	8.179	8.67***	9.10***
Within R^2	0.23	0.256	0.36	0.37	0.202	0.221	0.32	0.36
C-test of endogeneity (*p* value)	0.702	0.52			0.042	0.126		
Weak-ID test (*F* instruments)	39.20	25.42	110.75	60.1	38.67	23.00	47.11	33.87
Stock–Yogo weak ID test (critical val 15% max IV size)	8.96	11.59	16.38	19.93	8.96	11.59		
Partial R^2	0.12	0.15	0.27	0.28	0.14	0.16	0.2	0.25
AR Weak-ID-robust *F* (*p* value)	0.10	0.04	0	0.02	0.00	0.00	0.02	0
AR Weak-ID-robust χ^2 (*p* value)	0.09	0.03	0	0.01	0.00	0.00	0.01	0
J-statistic (*p* value)		0.13		0.48		0.12		0.06
No. of observations	862	822	637	620	817	784	573	550
No. country-sector effects	150	143	129	123	148	141	119	113

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

Table 4
Weak PH – *R&D* IV regression – second stage results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PACE-inst	−0.234	−0.034	−0.448	−0.125	–	–	–	–
	(0.198)	(0.137)	(0.318)	(0.198)				
PACE-inst(-1)	–	–	–	–	−0.086	−0.134	−0.403**	−0.475***
					(0.109)	(0.102)	(0.175)	(0.184)
$VA(-1)$	0.100*	0.05	0.123**	0.093	0.086	0.079	0.156	0.190**
	(0.048)	(0.067)	(0.056)	(0.102)	(0.069)	(0.068)	(0.009)	(0.102)
$GOVR\&D(-1)$	−0.20	−0.16	−0.04	0.034	−0.244	−0.26	−0.086	−0.077
	(0.191)	(0.171)	(0.211)	(0.150)	(0.149)	(0.156)	(0.180)	(0.202)
$KR\&D(-1)$	–	–	0.674***	0.563***	–	–	0.665***	0.693***
			(0.191)	(0.191)			(0.157)	(0.151)
$EXP(-1)$	–	–	0.413**	0.397**	–	–	0.348**	0.291**
			(0.164)	(0.174)			(0.141)	(0.153)
$IMP(-1)$	–	–	−0.161	−0.168	–	–	0.494***	0.500***
			(0.222)	(0.252)			(0.172)	(0.191)
$DR(-1)$	–	–	1.589	−0.337	–	–	−0.228	−0.438
			(9.122)	(1.985)			(0.678)	(0.719)
$BR(-1)$	–	–	0.848	−0.372	–	–	0.141	0.254
			(8.521)	(0.901)			(0.489)	(0.508)
No. of observations	693	629	498	480	654	620	509	492
No. of country-sector	127	120	108	102	124	117	104	98

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

Table 5
Weak PH – patents IV regression – second stage results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PACE-inst(−1)	0.116*	0.131**	0.073**	0.063**	–	–	–	–
	(0.067)	(0.056)	(0.033)	(0.031)				
PACE-inst(−2)	–	–	–	–	0.192***	0.170***	−0.060*	−0.052*
					(0.048)	(0.052)	(0.032)	(0.031)
VA(−1)	0.036	0.039	−0.052	−0.051	−0.059**	−0.056*	−0.008	−0.01
	(0.043)	(0.040)	(0.031)	(0.034)	(0.028)	(0.029)	(0.039)	(0.040)
GOVR&D(−1)	0.308***	0.333***	−0.073	−0.082	0.212**	0.202**	−0.156**	−0.112*
	(0.091)	(0.078)	(0.062)	(0.061)	(0.090)	(0.091)	(0.072)	(0.056)
KPAT(−1)	–	–	0.528***	0.535***	–	–	0.537***	0.518***
			(0.073)	(0.071)			(0.091)	(0.085)
EXP(−1)	–	–	0.079	0.062	–	–	0.083	0.07
			(0.056)	(0.061)			(0.090)	(0.091)
IMP(−1)	–	–	0.345***	0.346***	–	–	0.365***	0.418***
			(0.110)	(0.111)			(0.133)	(0.132)
DR(−1)	–	–	−0.028	−0.036	–	–	0.108	−0.052
			(0.163)	(0.154)			(0.231)	(0.180)
BR(−1)	–	–	0.291*	0.307*	–	–	0.397	0.580**
			(0.170)	(0.171)			(0.261)	(0.256)
No. of observations	862	822	609	592	817	784	546	523
No. of country-sector	150	143	122	116	148	141	112	106

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: *$p<0.1$, **$p<0.05$, ***$p<0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

determinants 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 at time *t*. The assumption is that, within each sector and year, the level of efficiency, among other factors, depends on technological and organizational transfers from the technology leader country. This variable aims at capturing the link between *TFPG* 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, *TFPG* in the frontier country is assumed to lead to faster *TFPG* in follower countries by widening the production possibility set. Along similar lines, we assume that the technological gap variable captures the extent to which *TFPG* 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 *TFPG*.[17]

4.2.1. Estimation results

The timing of the productivity impact of environmental regulation involves asking how soon we can expect to see it. As to the direct effect of *ER* through additional input costs, that is likely to be prompt. As to the induced *R&D* effect, previous empirical work suggests that *R&D* brings about productivity growth with a lag of one to three years (see, for example, Griffith et al. 2004). Moreover, as argued in the previous section, the potential impact of environmental regulation on *R&D* is likely to be lagged as well. Thus, we include *ER* in the reduced-form productivity Eq. (3) with different lags, ranging from one to four years (Table 6).

Results of the estimation of the reduced-form model where we regress *TFP* against one- and two-years lagged *PACE* and the set of controls are presented in columns 1–4 of Table 6. As in the previous section, we use the model with country-sector fixed effects and consider both *TFP* level (columns 1–2) and *TFPG* (columns 3–4) as dependent variables. Across all specifications we find no evidence of a statistically significant effect of environmental policy stringency on factor productivity. Regardless of the controls used, the *PACE* variable always remains insignificant. As to the other controls, only those directly attributable to the *TFP* convergence model turn out to be significant.

We may also want to verify the impact of generic innovation on the level of *TFP* in connection to the empirical work carried out in the previous section under the weak PH. As innovation proxies we therefore use the fitted values of *R&D* and *PAT* variables predicted from the innovation equations of Table 1. The results of the FE estimation of this *TFP* level model are reported in columns 5–8 of Table 7.[18] They do not favor 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 the patent variable is negative but only weakly significant.[19] 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 might decrease its productivity.

4.2.2. Endogeneity of PACE

The potential endogeneity of *PACE* could be a concern also in the productivity equations. Firstly, in the FE specification the assumption that omitted common determinants of the 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 cannot capture these factors with the country-sector fixed effects. Secondly, endogeneity of contemporaneous *PACE* could arise in productivity equations for 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 environmental regulations, inverse causality would entail a positive

[17] Also in this case, due to productivity data availability, we lose some observations.

[18] Bootstrapped standard errors were applied to properly account for the inclusion of generated regressors.

[19] The results are robust to using different lags of R&D and *PAT*, to using the original R&D and *PAT* values (rather than predicted), and to using the stocks of R&D and *PAT* instead of the flows.

Table 6
Strong PH – TFP FE regression and two-stage models.

	FE regression				Two-stage model			
	TFP level		TFP growth		TFP level		TFP growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PACE(−1)	−0.007	–	0.004	–				
	(0.009)		(0.001)					
PACE(−2)	–	−0.001	–	0.001				
		(0.011)		(0.003)				
R&D-pred(−1)					−0.068	–	−0.001	–
					(0.056)		(0.003)	
PAT-pred(−1)					–	−0.078*	–	0.002
						(0.040)		(0.004)
TFPG-frontier			0.232**	0.226**			0.179	0.210**
			(0.109)	(0.112)			(0.113)	(0.002)
TFP-gap(−1)			0.078***	−0.071**			0.020***	0.007
			(0.029)	(0.031)			(0.014)	(0.009)
VA(−1)	−0.012	−0.017	0.003	0.008	−0.055	−0.018		
	(0.019)	(0.030)	(0.008)	(0.012)	(0.038)	(0.031)		
IMP(−1)	−0.019	−0.047	−0.02	0.006	−0.032	−0.087	0.008***	−0.005
	(0.067)	(0.075)	(0.029)	(0.027)	(0.121)	(0.089)	(0.002)	(0.001)
EXP(−1)	−0.006	−0.016	0.04	0.035	−0.03	−0.043	0.006**	0.003
	(0.061)	(0.063)	(0.030)	(0.021)	(0.067)	(0.056)	(0.003)	(0.004)
DR(−1)	0.035	0.146*	0.039	0.087***	0.328	0.167	−0.023	0.058
	(0.041)	(0.089)	(0.042)	(0.028)	(0.253)	(0.239)	(0.078)	(0.056)
BR(−1)	−0.027	−0.15	−0.064	−0.052	−0.378*	0.115	−0.003	−0.042
	(0.089)	(0.109)	(0.051)	(0.048)	(0.209)	(0.217)	(0.092)	(0.067)
F	5.38***	6.03***	2.85***	6.65***	0.23	0.2	0.16	0.18
R^2	0.21	0.17	0.16	0.18	296	354	296	354
No. of observations	476	432	476	432	84	86	84	86
No. of country-sector effects	95	95	95		–	–	0.179	0.210**

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

correlation 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 errors.

To overcome the potential endogeneity problem we adopt an instrumental variable (IV) approach similar to the one used in the innovation equations. We estimate the effect of environmental costs on innovation performance using 2SLS and optimal IV-GMM estimators in the just identified and the overidentified equations, respectively, including country-sector and time fixed effects. The instruments are the same as before.

Table 7 reports the results of the first-stage IV regression. We present the results of the *TFP* level model in columns 1–4 and of the *TFPG* model in columns 5–6 respectively. The coefficients of $PACE/VA_{-j}$ and $PACE/VA_{-j} \times EI_{pre}$ are strongly significant across all the specifications. All the tests reported at the bottom of the table confirm relevance and validity of the instruments, as in the case of the IV estimation of the innovation equations.

The results of the second-stage IV regression, presented in Table 8, are not completely in line with those of Table 7 where we did not account for the potential endogeneity of *PACE*. The effect of environmental regulation remains negligible and insignificant in the *TFPG* regression.[20] As to the *TFP* level model, we find a negative, weakly significant effect of one-year lagged *PACE*, but not of two-year lagged expenditures. We believe that these results should be taken with care, as the FE model does not support as a whole the “innovation channel” of productivity growth.[21]

5. Discussion

When looking at the weak PH we conclude that environmental regulation leads to an increase in patent applications, but has no impact on *R&D* expenditures. These findings are in contrast with those of earlier papers, beginning with those of Jaffe and Palmer (1997). As to patents, a number of previous papers show that environmental regulation positively impacts environmental patenting. We complement this result by showing that for our sample of European countries environmental regulation results in an enhancement of overall patent activity (and not only environmental patents). Our evidence suggests the following: environmental regulation stimulates environmental *R&D* spending which displaces non-environmental *R&D*, but does not result in lower overall *R&D* levels (hence, *PACE* is not significant in the *R&D* equation). This increased environmental *R&D* is applied as an input in the production of knowledge resulting in more patent applications. The increased patent activity could result from two different processes. On one hand, it could be fully attributable to environmental patents. This would be the case if, for example, environmental innovation was inherently more patent-intensive than overall innovation. On the other hand, this shift of the focus

[20] *PACE* beyond the one-year lag has no effect on *TFPG* in the IV regression.

[21] Several robustness checks can be found in Rubashkina et al. (2014).

Table 7
Strong PH – TFP IV regression – first stage results.

	TFP level				TFP growth	
	(1)	(2)	(3)	(4)	(5)	(6)
$PACE/VA_{-j}(-1)$	0.683***	0.580***	–	–	0.677***	0.560***
	(0.078)	(0.089)			(0.081)	(0.093)
$PACE/VA_{-j} \times EI_{pre}(-1)$	–	0.508***	–	–	–	0.564***
		(0.189)				(0.181)
$PACE/VA_{-j}(-2)$	–	–	0.616***	0.509***	–	–
			(0.078)	(0.103)		
$PACE/VA_{-j} \times EI_{pre}(-2)$	–	–	–	−0.501**	–	–
				(0.211)		
$VA(-1)$	0.339**	0.447***	0.397*	0.452**	0.333**	0.456***
	(0.131)	(0.139)	(0.201)	(0.182)	(0.143)	(0.151)
$IMP(-1)$	0.707**	0.793***	0.867***	0.868***	0.633**	0.697**
	(0.298)	(0.267)	(0.332)	(0.311)	(0.278)	(0.281)
$EXP(-1)$	0.904***	0.852***	−0.406	−0.43	0.890***	0.817***
	(0.272)	(0.264)	(0.361)	(0.349)	(0.267)	(0.261)
$DR(-1)$	−1.106	−1.075	1.202***	−1.241***	−1.038	−1.001
	(0.881)	(0.878)	(0.278)	(0.302)	(0.890)	(0.889)
$BR(-1)$	1.308	1.293	1.322**	1.244**	1.301	1.298
	(1.156)	(1.160)	(0.535)	(0.541)	(1.142)	(1.129)
F-statistics	11.36***	13.04***	16.72***	16.03***	10.97***	11.83***
Adjusted R^2	0.4	0.42	0.34	0.35	0.41	0.43
C-test of endog.(p-value)	0.201	0.41	0.328	0.749	0.301	0.156
F instruments	74.02	51.04	53.05	34.21	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
Partial R^2	0.28	0.3	0.23	0.25	0.28	0.3
p-Value Anderson–Rubin F-test	0.04	0.14	0.28	0.32	0.65	0.75
p-Value Anderson–Rubin χ^2 test	0.04	0.12	0.27	0.3	0.64	0.74
p-Value J-statistic		0.28		0.21		0.51
No. of observations	467	467	413	413	467	467
No. of country-sector effects	86	86	76	76	86	86

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

of *R&D* activities to green innovation might indeed push firms to overcome inertia and to become more efficient in their non-environmental innovation production. Our analysis suggests that both these channels could be at work, but cannot cast definitive results on the strength of these two effects.[22]

This notwithstanding, the evidence we present has important policy implications. Increased environmental regulation as proxied by *PACE* in our sample did not result in lower innovation levels. Hence, there is support for the hypothesis that sectors somehow

[22] The issue of environmental innovation crowding-out non-environmental innovation has been investigated, not necessarily with a specific reference to the PH, by Gray and Shadbegian (1998), Roediger-Schluga (2003), Kneller and Manderson (2012), Popp and Newell (2012). Interestingly, these studies all find evidence in favor of a crowding-out effect.

Table 8
Strong PH – TFP IV regression – second stage results.

	TFP level				TFP growth	
	(1)	(2)	(3)	(4)	(5)	(6)
PACE-inst(−1)	−0.020*	−0.014*	–	–	−0.003	−0.004
	(0.009)	(0.010)			(0.009)	(0.011)
PACE-inst(−2)	–	–	−0.013	−0.005	–	–
			(0.011)	(0.009)		
TFPG-frontier	–	–	–	–	0.241**	0.245***
					(0.101)	(0.094)
TFP-gap(−1)	−0.007	−0.008	−0.012	−0.019	0.007	0.007
	(0.022)	(0.021)	(0.029)	(0.025)	(0.007)	(0.012)
VA(−1)	–	–	–	–	0.084***	0.085***
					(0.033)	(0.032)
IMP(−1)	−0.014	−0.022	−0.041	−0.072	−0.018	−0.017
	(0.060)	(0.063)	(0.061)	(0.056)	(0.034)	(0.031)
EXP(−1)	−0.012	−0.001	−0.02	0.001	0.036	0.035
	(0.053)	(0.046)	(0.055)	(0.047)	(0.032)	(0.019)
DR(−1)	0.027	0.029	0.136*	0.148*	0.035	0.035
	(0.041)	(0.039)	(0.080)	(0.078)	(0.041)	(0.038)
BR(−1)	−0.012	−0.023	−0.13	−0.153	−0.055	−0.054
	(0.078)	(0.076)	(0.092)	(0.103)	(0.051)	(0.0047)
No. of observations	467	467	413	413	467	467
No. of country-sector effects	86	86	76	76	86	86

Notes to the table: (a) all variables in logs; (b) coefficient estimates from *FE* estimation; (c) country-year fixed effects and full set of time dummies included in all models; (d) robust standard errors (clustered on the sector-country unit) in parentheses; (e) significance: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$; and (f) the data on *EXP*, *IMP*, *DR* and *BR* are not complete, therefore we lose some observations when adding these covariates in the regressions.

adapt to tighter regulation, by either shifting inputs or increasing productivity, in such a way that it does not impair the output of their innovative activity.

Assessing the validity of the strong PH is admittedly more difficult, both conceptually and statistically. Conceptually, for instance, one aspect on which Porter is silent is the possibility of a Jevons Paradox or Khazzoom–Brookes effect of environmental regulation when positively affecting a firm's profitability and competitiveness. Indeed, the strengthened position of firms may induce them to expand so as to result into increased pollution. Statistically, there are several proxies for competitiveness or profitability, from real (productivity, market entry and exits) to monetary-financial (price-cost margins, profits, Tobin's *q*) ones. In our investigation of *PACE* effects on *TFP* levels or growth of European manufacturing sectors, we find that more stringent environmental regulation does not harm productivity either in one-year or in two-year period. Rather, the overall productivity effect is neutral. On the whole, potential positive effects on firms' innovation activity appear not to be able to offset the negative effect of additional compliance costs. We thus fail to find support in favor of the strong Porter Hypothesis. From a policy perspective, this should somehow ease concerns that European manufacturing sectors could be penalized because of increased domestic environmental policy stringency. The effect of environmental policy is indeed not comparable to the effect of other factors which would push firms to relocate production, such as lower foreign wages or capital costs.

Overall, our results confirm that the EU strategy of pursing green growth, namely reconciling the need for a more sustainable use of resources with sustained economic growth, is indeed possible and plausible. Of course, policy interventions to this end need to be appropriately designed, and concerns about enacting efficient policies that do not stifle competitiveness should always be present in the policy debate.

6. Concluding remarks

This paper has provided fresh new econometric evidence on the nexus between environmental regulation and competitiveness, as captured by innovation activity and productivity, allowing to shed further light on the well-known Porter Hypothesis in both its weak and its strong versions. The analysis is based on a panel of industrial sectors across seventeen European countries over the period of 1997–2009. Only few papers offer this comprehensive view, and even fewer do so in the context of manufacturing sectors of European countries. This is both interesting and relevant, as environmental regulation in the European Union has increased since the late 80s.

Another important feature of the paper is that it explicitly accounted for the potential endogeneity of our proxy of environmental policy, *PACE*, in the investigation of the environmental regulation-economic performance nexus. Only a handful of papers seem to have worried about this problem, which basically affects all proxies for policy stringency, not limited to environmental policy.

Our conclusions are that there is evidence in favor of the weak PH in European manufacturing sectors. More precisely, we find support in the case of patent applications but not of total *R&D* expenditures. The overall productivity effect of regulation becomes neutral when searching for a strong PH effect. These results often contrast with the limited available evidence for European sectors. Furthermore, we show that not controlling for the endogeneity of *PACE* may lead to biased estimates and may reverse the interpretation of the environmental regulation effect on economic competitiveness.

Our research highlights some important avenues for further research. One limitation of this paper is the limited coverage due to the availability of *PACE* data and of the data used to construct the productivity proxies. Large economies of the EU, such as Germany, France and Italy could not be included. and the effect of the increasing number of recent environmental policies that entered into force after 2006 as consequence of EU-wide environmental strategy could not fully be captured. In this direction we will focus our future research effort.

Related to the above problem is the issue of the search for suitable measures of environmental regulation. The debate surrounding this issue has been recently intensifying and so has research (Brunel and Levinson, 2013; Nesta et al., 2014; Galeotti et al. 2014). This issue is not in principle limited to the environmental area, but more generally it applies to any empirical analysis of the impact of policies on economically relevant variables.

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Appendix A. Classification of industrial sectors and summary statistics

See Table A1–A4.

Table A.1
Classification of industrial sectors.
Source: International Standard Industrial Classification of all economic activities.

#	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

Table A.2
Summary statistics (1997–2009).
Source: our own computations based on the EUROSTAT, the EUKLEM, the OECD STAN, the OECD ANBERD and the WIOD datasets.

Variable	Unit	Mean	Std. dev.	Min	Max
PACE/VA	percent	3.63	4.56	0.05	49.13
PACE/GO	percent	0.92	1.02	0.02	12.60
R&D/VA	percent	2.86	4.04	0.00	34.36
PAT/VA	pat/bln.euro	12.73	20.28	0.00	148.88
TFP		1.19	0.44	-0.39	2.06
TFPG (growth)		0.01	0.04	-0.55	0.30
GOVR&D	percent	1.28	0.46	0.36	2.08
KPAT/VA	pat/bln.euro	90	144	0.00	1282
KR&D/VA	percent	22.11	34.26	0.00	219.15
EXP	percent	0.60	1.14	0.05	15.69
IMP	percent	0.33	0.18	0.04	0.97
DR	percent	0.08	0.07	0.00	1.00
BR	percent	0.09	0.08	0.00	1.00
GDPpc	euro	18303	8119	4600	48000
EI	toe/bln.euro	1.16	2.49	0.02	42.41

Table A.3
Summary statistics of the main variables by country (1997–2009).
Source: our own computations based on the EUROSTAT, the EUKLEM, the OECD STAN, the OECD ANBERD and the WIOD dataset.

Country	*PACE/VA*	*PACE/GO*	*R&D/VA*	*PAT/VA*	*TFP*	*TFPG*
Bulgaria	5.28	1.14	–	5.13	–	–
Cyprus	3.00	0.84	–	11.40	–	–
Czech Republic	4.37	0.74	1.87	6.89	1.02	0.02
Estonia	3.28	0.95	2.16	12.88	–	–
Finland	2.79	0.78	4.85	25.49	1.27	0.02
Hungary	3.68	1.03	1.50	7.79	1.02	0.00
Lithuania	3.46	0.78	–	4.90	1.01	0.02
Netherlands	4.38	0.84	4.02	38.86	1.17	0.01
Norway	2.81	0.88	4.36	16.95	–	–
Poland	3.78	0.12	0.42	2.21	1.03	−0.01
Portugal	2.88	0.63	1.19	4.01	0.98	0.00
Romania	5.85	1.35	3.12	1.83	–	–
Slovakia	3.62	0.82	2.06	4.11	–	–
Slovenia	3.59	0.83	2.47	12.07	1.32	0.01
Spain	2.01	0.48	2.22	6.73	1.09	0.01
Sweden	5.14	1.73	–	30.84	1.23	0.01
United Kingdom	2.54	0.76	5.49	15.03	1.55	0.02
Total	3.63	0.92	2.86	12.73	1.19	0.01

Table A.4
Summary statistics of the main variables by sector (1997–2009).
Source: own computations based on the EUROSTAT, the EU KLEM, the OECD STAN, the OECD ANBERD and the WIOD.

Sector	*PACE/VA*	*PACE/GO*	*R&D/VA*	*PAT/VA*	*TFP*	*TFPG*	Energy intensity
1	2.60	0.63	1.05	4.15	1.06	0.01	0.37
2	1.52	0.57	1.25	4.56	1.12	0.01	0.30
3	2.38	0.64	0.48	0.90	1.21	0.01	0.56
4	3.25	1.07	0.60	2.17	1.31	0.01	0.69
5	9.49	1.43	4.88	19.17	0.29	0.01	3.96
6	4.03	1.16	8.17	36.97	1.44	0.01	1.20
7	3.45	1.29	0.99	7.42	1.67	0.02	1.39
8	6.08	1.20	1.90	11.93	1.40	0.01	2.37
9	1.16	0.37	5.99	29.10	1.04	0.01	0.10
Total	3.63	0.92	2.86	12.73	1.19	0.01	1.16

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