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Abstract. This paper represents an empirical investigation of the "weak" and "strong" Porter 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 "strong" PH. 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 "weak" PH in line with most of the literature. On the other front, we find no evidence in favor or against the "strong" PH, as productivity appears to be unaffected by the degree of pollution control and abatement efforts.

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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 the 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 environmental regulation, firms also incur in indirect (opportunity) costs because they cannot invest in other profitable endeavors (Ambec, Cohen, Elgie,and Lanoie, 2013).

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. Their theory, which is referred to as Porter Hypothesis (PH), was initially formulated in rather general terms. Firms face market imperfections, such as imperfect and asymmetric information, organisational inertia or control problems. 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. Regulation-induced innovation would 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, possibly also with respect to firms in foreign countries not subject to similar regulation.

Since the early 1990s proving or disproving the PH, which has important implications for policy making and firms performance, has been the focus of many empirical contributions (see Rubashkina, 2013 for a review). Specifically, the PH has been 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.

Most of the empirical studies, however, focus on the US, while the evidence for Europe is scant. This is particularly troublesome because, given the recent European policy developments, the validity of the PH is of great relevance for EU countries. Since the end of 1980s the European environmental policy became more stringent.[1] Today, integration of environmental protection into other EU policies is seen as a necessary step. EU members 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. Moreover, in light of the economic crisis, the concept of "green recovery" (Edenhofer and Stern, 2009) gained the centre stage. In this respect, the European Commission argues that environmental policies and increased competitiveness are not mutually exclusive, but can indeed strengthen one another (European Commission, 2010).

Since the PH has not been unambiguously (dis)proven, many worry that environmental regulation will place an excessive burden on European industries, thereby stifling growth and damaging their

1 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 (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 Integrated Pollution Prevention and Control Directive (96/61/EC, 1996), the Ambient Air Quality Directive (96/62/EC, 1996), the Water Framework Directive (2000/60/EC, 2000) and the National Emission Ceilings Directive (2001/81/EC, 2001). They were followed by the introduction of the EU Emission Trading Scheme (Directive 2003/87/EC) and by the directives of the 2020 Climate and Energy Package on CO_2 emission reduction (2009/29/EC, 2009) and renewable energy (2009/28/EC, 2009).

competitiveness in an increasingly global market place. Testing the link between environmental regulation and competitiveness indicators is therefore particularly relevant for Europe, where country-specific dynamics is likely to play a big role. 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.

This paper investigates the PH using cross-country sector-level data for European countries in order to assess empirically whether environmental regulation enhances or stifles sectoral innovation and productivity.

We contribute to the literature in several ways. First, we provide a combined assessment of the impact of environmental regulation on both innovation and competitiveness in the context of the PH for European industries. We thus look at both the "weak" and at the "strong" versions of the PH. Previous contributions have focused separately either on the impact of regulation on environmental innovation or on competitiveness. When looking at the "weak" PH the focus of previous studies was on the environmental regulation impact on energy efficiency and renewable energy innovation; when addressing the "strong" PH the proxy for competitiveness was typically represented by exports and generally focused on the US. The contributions on the "weak" PH conclude that environmental innovation positively responds to environmental policy. However, they don't explore the impact of environmental policy on overall innovation, thereby ignoring issues linked with opportunity costs of environmental innovation. We thus address two important unexplored questions regarding the EU manufacturing sectors: (a) we assess whether environmental policies result in higher environmental innovation but at the cost of reducing overall innovation and (b) we focus on the impact of environmental policy on the value added in manufacturing.

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 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. The only other contribution addressing a similar research question is Franco and Marin (2013). We improve on their research by going a great lengths towards accounting for the endogeneity of the policy proxy we adopt in our empirical framework.

Third, we use pollution abatement and control expenditures (*PACE* henceforth) at the sectoral level as an environmental policy indicator. *PACE* measure the consequence of government environmental policies and regulations and include the flow of investment and current expenditures directly aimed at pollution abatement and control. Although there is an intense discussion on the pros and cons of alternative measures of policy stringency, few are characterized by the property of sectoral variability, certainly a plus in the investigation of the PH. Unlike other commonly used proxies of environmental policy (Nesta, Vona, and Nicolli, 2014), *PACE* data 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 sectors. Moreover, *PACE* data were used in the seminal paper by Jaffe and Palmer (1997) in their investigation for US sectors: we implement their approach when assessing European industries' innovation activity. Finally, we recognize the potential endogeneity of *PACE* and implement an instrumental variable approach. Only a handful of papers have tackled this important issue: not accounting for the endogeneity of environmental policy proxies may lead to biased estimates of the effects of environmental regulation on economic performance.

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

2. Related Literature

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. The first paper to look at the relationship between environmental regulation and patent activity is Lanjouw and Mody (1996) which looked at the data also for Japan and Germany. No econometric analysis was, however, conducted. Formally testing of the innovation impact was first carried out by Jaffe and Palmer (1997), who 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 for the period 1973-1991 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-level or sector-level US data they investigated the link between *PACE* and environmental patents (see, for example, 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, 2003), 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. Carrión-Flores and Innes (2010) examine the link between environmental patents and emissions, which proxies for environmental policy stringency, using data for 127 manufacturing industries over a 16-year period (1989-2004). 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. Kneller and Manderson (2012) focus on UK manufacturing industries and relate innovation, proxied by either R&D or capital investment, to expenditures on end-of-pipe pollution control and the operation of pollution control equipment.

Constantini and Crespi (2008) investigated the "strong" PH in the energy sector of seventeen European countries plus Japan, Canada and US. They focus on export effects and employ 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, Costantini and Mazzanti (2012) extend the investigation of the environmental regulation-export nexus to a broad range of manufacturing sectors in the EU-15 using *PACE* and environmental tax share as policy variables. Finally, a very recent contribution by Albrizio and Zipperer (2014) considers seventeen OECD countries and consistently finds a significant and positive effect of a pollution intensity index on total factor productivity at both sector and firm level.

There are aspects to note concerning the EU-based studies just mentioned. First, in many cases they are country-level analyses. As a result, they cannot account for heterogeneity in sectoral responses to regulation. Sometimes, as in Costantini and Mazzanti (2012), the study does have a sectoral dimension, but the environmental regulation variables employed is country-specific and does not exhibit any sectoral variation. Second, most studies test 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 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. 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 allegedly the most controversial statement of the PH.

Finally, it has been noted that only very few papers in this area recognize the potential endogeneity of *PACE*, unlike many others including Jaffe and Palmer (1997). 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 through an appropriate instrumental variable approach may bias estimates of environmental regulation effects on economic performance.[2] This drawback is also shared by Franco and Marin (2013), a very recent contribution that looks at both the impact on innovation and total factor productivity using energy tax intensity (energy tax revenues per unit of value added) as a proxy of environmental policy stringency.[3]

2 Also in the related, large literature on the pollution heaven hypothesis that investigates the impact of environmental regulation on the relocation of manufacturing enterprises few papers account for endogeneity of environmental policy variables (Xing and Kolstad, 2002; Ederington and Minier, 2003; Levinson and Taylor, 2008).

3 Their sample covers 13 manufacturing sectors of 7 European countries over the period 2001-2007. Our data are based on 7 *PACE* sectors of 17 European countries for the years 1997-2009.

In this paper we test for the validity of the PH in both its weak and strong versions using data on individual manufacturing sectors of European countries. We use data with a wide sectoral and country coverage and, in keeping with most of the previous literature, we use sector-level data on *PACE*, a feature not shared by many alternative policy stringency availables. The endogeneity of this policy indicator is accounted for and appropriately dealt with. These data have not been previously exploited for European country-sectors.

3. Competitiveness and Environmental Policy Indicators

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

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

where C is a competitiveness indicator, ER is an environmental regulation stringency variable and Z are other control variables. Equation (1) is the basis of our empirical investigation. To operationalize it we have to specify the variables with which we capture the notions of competitiveness and of environmental policy stringency, together with the controls to introduce.

Competitiveness C is represented by technological innovation TI in the weak version of the PH and by factor productivity FP in the strong version. We describe the proxies we use for these indicators in the following subsections.

3.1 Innovation Proxies

To test for the impact of environmental regulation on technological innovation, in keeping with Jaffe and Palmer (1997) we proxy TI activity using both R&D expenditures and patent statistics. 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, 2012).[4] We complement this source with data from EUROSTAT (EUROSTAT, 2012a) for some missing countries like Bulgaria, Sweden, Slovakia and the UK. The data are available for fourteen countries over the period 1998-2009.[5]

Conversely, patent statistics approximate the output of the knowledge production function (see, for example: Joutz and Gardner, 1996; Johnstone, Hascic, and Popp, 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 use 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 from the EUROSTAT Patent statistics database (EUROSTAT, 2012b).[6] Patent applications are assigned to a country according to the inventor place of residence, using fractional counting if there are multiple inventors. In view of the econometric analysis this implies that patents do not have to be treated as a count variable, but data are real-valued continuous observations. Data on sectoral patent applications are available for all EU countries for the period 1977-2009.

3.2 Productivity Proxies

To test the impact of environmental regulation on *FP* we mainly follow Gray and Shadbegian (1993, 2003) and use Total Factor Productivity (*TFP*) to proxy for sectoral economic

4 The R&D data from EUROSTAT are originally reported in current Euros, so we deflate them with the 2005 GDP deflator.
5 A concern related to cross-country comparability of the R&D data from the OECD ANBERD database 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.
6 EUROSTAT patent data are based on the EPO Worldwide Statistical Patent Database (PATSTAT). The data exclude 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.

performance/competitiveness (see also Albrizio and Zipperer, 2014). *TFP* shows the time profile of how productively combined inputs are used to generate gross output. Although conceptually *TFP* captures technical change, in practice it reflects also efficiency change, economies of scale, variations in capacity utilisation and measurement errors (OECD, 2001).

Following Inklaar and Timmer (2008), to compute our productivity measure we use data from the EU KLEMS database (EU KLEMS, 2009) and the WIOD Socio-Economic Accounts database (WIOD, 2012).[7] The EU KLEMS database provides Gross Output (*GO*), Value Added (*VA*), inputs indicators for capital, labor and intermediate inputs to construct *TFP* levels and growth rates. The EU KLEMS database has the advantage of providing capital and labor inputs both in absolute and in constant-quality index 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, 2003; Hamamoto, 2006; Lanoie, Patry and Lajeunesse, 2008), 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. We employ a “raw”

7 We provide details on the construction of *TFP* in Appendix C. Here, we only point to some major issues related with the computation of *TFP* which affect our empirical choices. We performed the analysis on the strong PH also using labor productivity as a widely used measure of productivity, in addition to *TFP*. We do not report results due space limitations and because we feel that *TFP* is a more appropriate measure of performance, at least in the present context.

TFP indicator that is not adjusted for the inputs' quality composition, which is available both in levels and growth rates for eleven countries of the sample, and a quality-adjusted *TFP* growth indicator, available only in growth rate terms and for eight countries of the sample.

3.3 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 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.[8] *PACE* data for the EU manufacturing sectors are available for the period 1997-2009.

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8 *PACE* distinguishes between nine different environmental domains: 1) protection of ambient air and climate, 2) wastewater management, 3) waste management, 4) protection and remediation of soil, groundwater and surface water, 5) noise and vibration abatement, 6) protection of biodiversity and landscapes, 7) protection against radiation, 8) research and development and 9) other environmental protection activities. *PACE* exclude expenditures on natural resource management and several activities, such as the protection of endangered species (fauna and flora), the establishment of natural parks and green belts and activities aimed at exploitation of natural resources (e.g., the drinking water supply). Other exclusions are expenditures intended either for workplace protection or for the improvement of production process for commercial or technical reasons, even when they have environmental benefits. Investment and current expenditure that have positive environmental effects without being directly motivated by environmental concerns. For example, investments in energy-saving equipment, that are made due to increases in energy prices are excluded. In statistical practice, the identification of such expenditure is difficult, particularly in the business sector, where firms may be unable to distinguish between the different investment motives. It is difficult to identify when pollution abatement is the actual motivation behind less wasteful use of raw materials. Therefore, the measurement of air and water pollution abatement expenditures may differ from this baseline.

To collect the data on these regulation variables we rely on two sources. When possible we use data on "environmental protection expenditures" from EUROSTAT (EUROSTAT, 2012c).[9] 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.[10] 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.

4. Descriptive Statistics

The period of analysis and the country sample have been selected on the basis of the data availability of our environmental regulation indicator. 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. [11]

The level of aggregation by industrial sectors varies across the five different data sources we used to collect our variables (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

9 When observations for one of the variables are missing for at most one or two sectors within a country-year we restore the missing values by taking the difference between total manufacturing and some of the available sectors (only eight *PACE* missing values were recovered using this procedure).
10 For sectors 2, 6, 8 and 9 we obtain the PPI as a Value Added weighted average of the PPI indices of the corresponding 4-digit level sectors. We also interpolated particular PPI missing values by applying the GDP deflator growth rate of the last available corresponding PPI value. For countries that do not report PPI such as Cyprus, Estonia, Portugal and Slovakia we instead adjust nominal *PACE* values using the GDP deflator from EUROSTAT.
11 We exclude the other EU countries as they do not provide the required data on environmental regulation.

macro sectors. The classification and the reference to the two-digit European NACE revision 1.1 sectoral classification are shown in Table 1.[12]

[Insert Table 1 about here]

Table 2 provides summary statistics of the main variables in the overall sample, while Table 3 provides statistics by country.[13] Looking at the competitiveness indicators we note striking differences 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).

[Insert Table 2 about here]

[Insert Table 3 about here]

Table 4 provides descriptive statistics by sector. Some sector, such as sector 5 ("Coke, refined petroleum products and nuclear fuel"), sector 6 ("Chemicals; rubber and plastic products") and

12 Definition, data sources and period of availability of all the main variables used in the present investigation are reported in Table A.1 of Appendix A.

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

sector 9 (“Machinery and equipment”), have patent and R&D intensities which are twice the average. Their patent intensity ranges between 19-36 patents per billion of Euro against an 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 respect 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. We also notice that these three sectors are characterized by high energy intensity, as reported in the last column of Table 4.[14] Therefore, energy intensive sectors appear to spend more on environmental expenditure regardless of environmental regulation stringency.

[Insert Table 4 about here]

5. Environmental Regulation and Innovation Activity: The “Weak” Porter Hypothesis

We begin our empirical analysis by studying the relationship between environmental regulation and innovative activity, while the impact of environmental regulation on productivity is analyzed in section 6.

5.1 Empirical Strategy

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

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

14 Energy intensity is defined as emission-relevant energy use (in TOE, tons of oil equivalent) 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).

where TI_{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 represented by *PACE* expenditures.[15] 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 for *ER* and public support to private *R&D*, as discussed below. Due to data availability the *R&D* and patent equations are estimated for the period 1999-2009 and 1997-2009, respectively.

To deal with factors that could affect a sector innovation performance we include a vector of sector- and country-level covariates (Z^{TI}). Sector-level covariates include value added (*VA*), the stock of knowledge stock (*KR&D* or *KPAT*), import penetration (*IMP*), export intensity (*EXP*), enterprises birth rate (*BR*) and death rate (*DR*). Country-level covariates include public support to private *R&D* ($R\&D^{GOV}$).

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. Among the determinants of innovation, a prominent role is played by technology push factors (Schumpeter, 1943; Schmookler, 1966; Horbach, Rammer, and Rennings, 2012). Thus, we add a knowledge stock variable (*KR&D* or *KPAT*) 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 to engage in innovative practices in the future (Baumol, 2002). The stock of knowledge is calculated using the perpetual inventory method (Verdolini and Galeotti, 2011) (see Appendix B). We include import penetration (*IMP*) as a proxy of external competition.

15 Alternatively we can regress the ratio *R&D/VA* or *PAT/VA* on the ratio *PACE/VA*. However, a measurement error in value added could cause equation (2) to exhibit spurious correlation. Nevertheless, we estimated the equation in ratio form as a robustness check. The results for PACE were very similar to those reported here and are not reported to conserve on space.

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, Cohen, and Mowery,1985). Therefore, the sign associated with the effect of external competition on innovation is a priori ambiguous. Import penetration is calculated as the ratio of imports 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). We add export intensity (*EXP*) which controls 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).[16] To control for the effect of sectors' structural change due to creations, deaths or relocations of enterprises on innovation intensity we incorporate enterprises birth (*BR*) and death (*DR*) rates in the equation. This structural changes might also affect environmental costs intensity. In particular, if enterprises shut down or relocate due to strict environmental policy, it is likely that *PACE* intensity decrease as the most burdened 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.[17] The data are obtained from EUROSTAT Detailed enterprise statistics on manufacturing subsections (EUROSTAT, 2012a).

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16 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 the 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 of these two countries are missing.

17 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).

Finally, 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 come from the GBAORD OECD database (OECD, 2012) which has the disadvantage of being reported only at the aggregate country level with no sectoral detail.

The control variables summarised by 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 section 5.3 below.

To test the dynamic effect of environmental regulation on innovation noted by several authors (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 engage 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 for contemporaneous, one and two years lagged effects of environmental policy due to different assumptions about the reaction time of firms 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 (se, for example, Brunnermeier and Cohen, 2003; Hamamoto, 2006; Johnstone, Hascic, and Popp, 2010). Given the different nature of R&D and patent data, we assume a different lag structure in the patents equation. Specifically, we assume that the whole innovation process from R&D investment to a patent application takes time and that environmental policy-induced innovations could be 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.

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*. 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. A related issue is whether to treat country-sector effects as fixed (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, though it uses only the within variation of the data, thereby leading to less efficient estimation. 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.[18]

5.2 Estimation Results

Tables 5 and 6 report the estimation results of the effect of environmental regulation, as proxied by *PACE*, on R&D efforts and patenting activity respectively. Columns (1)-(2) and columns (3)-(4) differ as they consider either a contemporaneous (resp. one-year lagged) or one-year lagged (resp. two-year lagged) impact of *PACE* on the innovation variable. As a starting point, columns (1) and (3) of both tables 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.[19]

[Insert Table 5 about here]

[Insert Table 6 about here]

The first and most relevant result emerging from Table 5 is that in no case is the impact of environmental regulation on R&D efforts statistically significant across all the specifications. On the contrary, according to Table 6 the effect of *PACE* on patent applications is always

18 We validated this choice with a Hausman test whose outcome, not reported in the tables for brevity, confirms that the FE model is preferred to the RE model.

19 It should be kept in mind that due to data availability issues the estimation of the *R&D* equations are carried out on a smaller country sample than that of the patent equations. In particular, we lose observations on three countries, namely Lithuania, Estonia and Cyprus. Therefore, the results of two innovation equations are not directly comparable. However, results available from the authors upon request show that the findings are robust to the use of homogeneous samples.

positive and significant. Depending on the specification, a 10% increase in *PACE* is associated with a 0,3-0,9% increase in number of patent applied for.[20] Taking together the results of *R&D* and *PAT*, we conclude that 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. These findings are in line with the literature pointing to a positive and significant impact of environmental regulation on innovation (Ambec, Cohen, Elgie, and Lanoie, 2013). However, they are in contrast with those of Jaffe and Palmer (1997), who find 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 a stimulus to one important input to the production of knowledge, butit does favour 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 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. External competition, measured by import intensity, has a negative and significant im- pact 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, while patent intensity is positively affected by opening of new enterprises. In several specifications the public support of private R&D, as measured by the share of public R&D in government budget, has positive effect on private R&D and patent behaviour.

5.3 Endogeneity of *PACE*

20 Several additional results are available from the authors upon request. Many of them are not reported because of space limitations. For instance, the results of Tables 5 and 6 do not change if we considered longer lags for *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. In fact, the endogeneity of the *PACE* could cause both downward and upward bias in the estimation of its effects. The assumption that omitted common determinants of the 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 cannot hope to capture these factors simply including 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 could *PACE* 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 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. 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).[21]

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 a vector that includes all the covariates of the previous tables and the average share of *PACE* intensity

21 If we go back to equation (1) and assume that *ER* is not observed, we can specify the following:

(i) $C = g(ER, Z)$

(ii) $PACE = g(ER, W)$

We can solve (ii) for *ER* as a function of *PACE*: $ER = g^{-1}(PACE, W)$ 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*.

for eight adjacent sectors of the same country excluding the current sector (*PACE/VA*$_{-j}$). This is taken as is and also interacted with pre-sample sectoral energy-intensity (year 1996), (*PACE/VA*$_{-j}$**EI*$_{pre}$).[22] 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 this instrument with its interaction with pre-sample sectoral energy-intensity as regimes of environmental regulation of energy-intensive sectors could differ from those of less intensive sectors within the same country: thus environmental policies of energy intensive sectors could stand out from policies of adjacent sectors. *EI* is defined as emission-relevant energy use (in tonnes of oil equivalent, TOE) over value added.[23] 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 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 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. 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-

22 We should note that using *PACE/VA*$_{-j}$ we lose several observations for Estonia, Lithuania, Slovenia, Slovakia and the UK where the *PACE* data across the sectors are not complete. Due to the nature of *EI*$_{pre}$ that is time invariant, we could not include it as an individual regressor in the first stage FE regression.

23 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). There are minor differences in the 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 lose observations on Norway when using *EI* as an instrument, due to the lack of sector-level data on energy use.

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 8 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-statistics that exceeds a widely used rule of thumb of 10 (Staiger and Stock, 1997) in columns (5)-(8) of Table 7 and in columns (1)-(4) of Table 8, 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-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 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-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 over-identifying restrictions are valid. Finally, the C-test rejects the null hypothesis that 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. The validity of the instruments are tested with Hansen's J-test. As the reported p-values are greater than 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.

[Insert Table 7 about here]

[Insert Table 8 about here]

Table 9 reports the second-stage estimation results of the *R&D* equation controlling for potential endogeneity of *PACE*. Columns (1)-(4) and (5)-(9) correspond to the specifications with current and one-year lagged *PACE*, respectively. In all cases the instrumented *PACE* is insignificant, in keeping with the results of the FE estimation in Table 5. 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: increasing regulation compliance expenditures by 10% leads to 4-5% decrease of overall *R&D*. Results available from the authors show that environmental regulation proxied by *PACE* does not affect R&D after one-year period.

[Insert Table 9 about here]

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% of regulation compliance expenditures increases the number of patent applications by approximately 0.1% in the one-year period. The same holds true for the two-years lagged effect of environmental regulation on patents. Other things equal, an additional 10% of regulation compliance expenditure decrease 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. 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. 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.

[Insert Table 10 about here]

Taking together the results of *R&D* and patent equations, we conclude that environmental regulation lead to an increase in patent applications. 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. The intuition is that under a stringent environmental regulation patenting such projects is likely to give a firm a first-mover competitive advantage. The IV results of both innovation equations highlight the upward bias of the lagged *PACE* coefficients in the FE estimation.

Our results on the *R&D* effect appear not to be 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 to bring about significant *R&D* enhancement effects both in the short- and the medium-term. As to patents, a number of previous findings show 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 find for our sample of European countries that environmental regulation results in enhancement of overall patent activity (and not only environmental patents).

6. Environmental Regulation and Productivity: The "Strong" Porter Hypothesis

We now turn to testing the relationship between environmental regulation and productivity following the same steps as in the previous section.

6.1. Empirical Strategy

Having found a link between environmental regulation stringency, as proxied by *PACE*, and the output of innovation, we further examine the relationship between regulation stringency and productivity. Environmental regulation affects productivity through a number of channels. On one hand, 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. On the other hand, as confirmed in the previous section, environmental regulation would affect the stock of knowledge which in turn could show up in productivity (the indirect effect). The latter effect is likely to appear in the medium-long run.[24]

In view of the multiple channels through which environmental regulation may affect productivity, the link between the former and the latter is traditionally modelled through reduced-form equations, where productivity is commonly measured by toal factor productivity (*TFP*) (Gray and Shadbegian, 1993, 2001; Lanoie, Patry, and Lajeunesse, 2008; Albrizio and Zipperer, 2014). In a reduced-form equation the coefficient associated with environmental regulation captures the overall effect of environmental regulation that operates through the different channels mentioned above. In particular, a positive coefficient of the environmental regulation variable would mean that an induced innovation effect, if existing, outweighs the additional input costs caused by environmental requirements resulting in enhanced productivity, thus supporting the “strong" Porter Hypothesis.

Following the literature and assuming a Cobb-Douglas three-input production function, our first reduced-form model is similar to (2) but relates the level of productivity to environmental regulation and to other controls:[25]

24 See the survey on the strong HP by Kozluk and Zipperer (2013).

25 We also employed labor productivity as a productivity indicator. The results are qualitatively similar to the one reported in the text and available from the authors upon request.

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

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 *TFP* computed as described in Appendix A. The productivity impact of environmental regulation is likely to be dynamic, which requires dealing with the presumed timing of that impact. Given that *ER* contributes to productivity growth, the question is how soon we can expect the environmental regulation effect. As to the direct effect of environmental regulation through additional input costs, it 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, Redding, and Van Reenen, 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 equation (3) with different lags, from one to four years.

To control for factors that could affect sectoral productivity we include in the vector of covariates enterprises birth and death rates, import penetration, export intensity, and value added. 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 could be understated. To control for the effect of a sector's structural change due to enterprises creations, deaths or relocations on the productivity of a sector we incorporate enterprises birth and death rates indicators in the equation. We also include import intensity 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, Redding, and Van Reenen, 2004), We supplement the vector of controls with export intensity 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 as a scaling factor.

The covariates, as before, 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.

An alternative version of (3) that we consider proxies *FP* with total factor productivity growth (*TFPG*), described in Appendix A, as there is no a priori reason to prefer, in the present context, TFP levels or *TFP* growth.[26] In the *TFPG* specification, in keeping with a large literature we supplement the vector Z^{FP} with a measure of *TFPG* at the frontier (*TFPG-frontier*) and a measure of the distance from the technological frontier (*TFP-gap*) that are found to be important determinants of productivity growth (Nicoletti and Scarpetta, 2003; Griffith, Redding, and Van Reenen, 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 the 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, we assume that *TFPG* in the frontier country leads to faster *TFPG* in follower countries by widening the production possibility set. We also include a technological gap that is

26 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 *TFPG* indicator is that we lose 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.

defined as the distance between *TFP* level of sector *j* in country *i* and the frontier country at time *t*. We assume that this 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*.

Finally, it is to be noted that, due to the availability of productivity data availability, estimation is carried out for eleven European countries, out of the 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 were estimated for seventeen countries.[27]

6.2 Estimation Results

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 Table 11.

[Insert Table 11 about here]

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, *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

27 Results available from the author upon request show that the results of innovation model are robust to using the sample of the productivity model.

therefore use the fitted values of *R&D* and *PAT* variables predicted from the innovation equations of Tables 5 and 6. The results of the FE estimation of this *TFP* level model are reported in Table 12.[28]

[Insert Table 12 about here]

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 patent variable is negative but only weakly significant.[29] 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.

6.3 Endogeneity

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 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}. Secondly, endogeneity of contemporaneous *PACE* could arise in productivity equations 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 a positive 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 error.

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28 Bootsrapped standard errors were applied to properly account for the problem of generated regressors.
29 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.

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 identified and the over identified equations, respectively, including country-sector and time fixed effects. The instruments are the same as before. 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 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 $PACE/VA_{-j}*EI_{pre}$ 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 the widely used rule of thumb equals to 10 (Staiger and Stock, 1997), thus not rejecting the joint significance of the excluded restrictions in the first-stage regression. Moreover, the 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, thus eliminating the concern that the excluded instruments are weakly correlated with the endogenous regressors (Stock, Wright, and Yogo, 2002; Stock and Yogo, 2005). Another weak instrument diagnostics that we use is Shea (1997)'s partial R^2 between *PACE* and the excluded instruments after controlling for the included instruments in the first-stage regression. Shea's partial R^2 are relatively large, thus indicating that the endogenous regressor is not weakly identified.

[Insert Table 13 about here]

The validity of the instruments are tested with Hansen's J-test of over-identifying restrictions. As the reported p-values 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 the 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 over-identifying restrictions are valid.

The results of the second-stage IV regression, presented in Table 14, are not completely in line with those of Table 12 where we did not account for the potential endogeneity of *PACE*. The effect of environmental regulation remains negligible and insignificant in the *TFPG* regression.[30] 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 whole the "innovation channel" of productivity growth.

[Insert Table 14 about here]

Taking together the productivity models results, we may conclude thus that more 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, 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.

7. Robustness

In this subsection we give account of several robustness checks we have carried on the regression models of both the weak and the strong PH. For space reasons we present no tables of empirical

30 The results available from the authors upon request show that the *PACE* beyond the one-year lag has no effect on *TFPG* in the IV regression.

results, which are nevertheless available from the authors. We note here that the outcome of these checks does not alter qualitatively the empirical results and the conclusions we reached.

A first concern in estimating the cross-country sector-level innovation and productivity models is the choice of the fixed effect. Inclusion of country-sector specific effects α_{ij} are to be preferred to control for country-sector time-invariant determinants of innovation and productivity levels and growth rates that are also likely to be correlated with the regressors. However, using country-sector specific effects implies that the parameters are identified only through the within dimension of the data. As one could see from the analysis of variance in Table A.2 of Appendix A, this could do in the case of *R&D* and *PAT*, while *TFP* has very low within variation (close to zero) which may entail imprecisely estimates in the FE regression. We re-estimated all models with an alternative specification that assumed two separate fixed effects, i.e. country effects α_i and sector effects α_j. This 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, and the like.

A second robustness check is related to lags of productivity effect of environmental regulation. As mentioned in Section 5, 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 tested for two-year lag effect of *PACE* in the *R&D* equation, for a three-year lagged *PACE* effect in the *PAT* equation, and for an impact of three and four year lagged regulation variable in the *TFP* level equation. This was done both not accounting and accounting for the endogeneity of *PACE*.

We use sample of equal dimension for all the equations presented above; we estimated the innovation equations using rations in value added for *PACE* and *R&D/PAT*; we experimented with labor productivity levels and growth rates; we experimented with effective energy tax rates instead of *PACE*. Generally speaking, our conclusions were unaffected by these extensions. We therefore summarize them hereafter.

8. 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. The analysis was based on a panel of industrial sectors across seventeen European countries over the period of 1997-2009. We have provided a combined assessment of both innovation and productivity impacts of environmental regulation, allowing to shed further light on the well-known Porter Hypothesis in both its weak and its strong version. 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 policy intervention in the European Union has become increasingly intense and widespread since the late '80s.

Another important feature of the paper is that it explicitly accounted for the potential edogeneity 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 results show that not controlling for the endogeneity of the *PACE* variable may lead to biased estimates and in some cases may reverse the interpretation of the environmental regulation effect on economic performance and competitiveness.

Succintly reporting the results of our econometric investigation, we fail to find a statistically significant effect of *PACE* on *R&D* efforts. Despite this fact, we find a positive and statistically significant patent effect of environmental regulation. These findings are robust to proper account of the endogeneity of *PACE*. 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* was found to bring about significant *R&D* enhancement effects both in the short- and the medium-term. One potential explanation for these contrasting evidence relates to the endogeneity of *PACE*, among other possible factors. As to 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 (de Vries and Withagen, 2005; Johnstone, Hascic, and Popp, 2010). However, they do not consider the opportunity costs of environmental innovation. Therefore, our results are not directly comparable with these studies.

Turning to productivity as a proper measure of competitiveness, our analysis fails to confirm a statistically significant role of environmental policy stringency on *TFP*, both in levels and growth rates. Accounting for *PACE* endogeneity does not alter this conclusion. The evidence that more stringent environmental regulation does not affect productivity is in contrast with the findings of early U.S. studies (Gray and Shadbegian, 1993, 2001) of depressing effects of environmental regulation on industrial productivity or with the results of the sector-level productivity investigations for other countries (Hamamoto, 2006; Lanoie, Patry, and Lajeunesse, 2008; Yang, Tseng, Chen, 2012) which concluded that stringent environmental policy spur productivity growth. This is also the finding of a recent invstigation conducted on ten sectors for seventeed OECD countries (Albrizio and Zipperer, 2014). Again, it is possible that one of the reason for this disagreement is the *PACE* endogeneity.

These contrasting results provide a strong motivation for further research into this time-honoured, relevant issue. One limitation of this paper to overcome refers to the coverage of European countries for which *PACE* data were available. Large economies of the EU that widely apply various regulatory instruments for pollution control and natural resource management, such as Germany, France and Italy could not be included. Moreover, due to data availability our productivity analysis was based on a few countries of interest (Czech Republic, Finland, Hungary, Netherlands, Slovenia, Spain, Sweden, United Kingdom, Lithuania, Poland, Portugal) and a 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.

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; Botta and Kozluk, 2014; Nesta, Vona, and Nicolli, 2014; Salini, Verdolini, Rubashkina, and Galeotti, 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.

In a nutshell our conclusions are that there is evidence in favour of the weak version of the PH in European manufacturing sectors. The overall productivity effect of regulation becomes however neutral when searching for a "strong" Porter Hypothesis effect.

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Appendix A: Definition of the Main Variables

Table A1: **Variables Definition and Data Sources**

Variable	Variable Description	Source	Data Availability
	Dependent Variables		
Patent	Total patent applications to EPO	EUROSTAT	1977-
R&D	Total R&D expenditures,	OECD ANBERD, mln.constant	1998-
TFP	Total Factor Productivity	EU KLEM	1970-
	Explanatory Variables		
PACE	PACE	EUROSTAT, mln.constant euro	1997-
PACE/V	Ratio of PACE to Value Added	EUROSTAT, percent	1997-
PACE/G	Ratio of PACE to Gross Output	EUROSTAT, percent	1997-
VA	Value Added	EUROSTAT, mln.constant euro	1995-
GO	Gross Output	EU KLEM, mln.constant euro	1977-
KPAT	Patent stock	EUROSTAT,	1993-
KR&D	R&D stock	OECD ANBERD, percent	1998-
GOVR&	Share of government R&D in	EUROSTAT, percent	1980-
IMP	Import intensity	WIOD, percent	1970-
EXP	Export intensity	WIOD, percent	1970-
BR	Birth rate	EUROSTAT, percent	1970-
DR	Death rate	EUROSTAT, percent	1970-
EI	Energy intensity	WIOD, percent	1970-

Table A.2: Variance Analysis of the Main Variables

Variable		Mean	Standard 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		0.067
TFP growth	overall	0.013	0.042
	between		0.011
	within		0.040

Appendix B: Construction of Innovation Stock

The stock is calculated using the perpetual inventory method (Verdolini and Galeotti, 2011) as follows:

(B1)
$$KTI_{ijt} = TI_{ijt} + (1-\delta)KTI_{ijt-1}$$

where TI = *(R&D, PAT)* and δ is the decay rate, set at a value of 0.1, as suggested by Keller (2002). The initial innovation stock is calculated as follows:

(B2)
$$KTI_{ijt_0} = \frac{TI_{ijt_0}}{\delta + \bar{g}_{ij}}$$

In equation (B2) we use t_0 as 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 data for earlier years are not available). In the patent equation the stock is computed using sectoral patent applications and t_0 = 1993.

Appendix C: Construction of Productivity Indicators

Assuming a Cobb-Douglas three 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 :

(C1)
$$TFP_{ijt} = \ln GO_{ijt} - \alpha_{ijt} \ln L_{ijt} - \beta_{ijt} \ln I_{ijt} - [1-(\alpha_{ijt} + \beta_{ijt})]\ln K_{ijt}$$

where *TFP* denotes the level of total factor productivity, *GO* is gross output, *L* is labor hours (of total engaged workers), *I* is intermediate inputs (including energy, service and material inputs), and *K* is net fixed capital stock,. 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., we assume constant returns to scale and perfect competition). This implies that the coefficients α and β are the shares of the 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 with regression techniques. We follow the first approach 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 labour compensation by the ratio of total employment to total employees in order to account for the compensation of self-employed. These are not registered in the National Accounts and, therefore, are 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-specific 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 backdate 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:

(C2) $$PPP_{ijt} = \frac{VA\_P_{ijt} / VA\_P_{ij1997}}{VA\_P_{USjt} / VA\_P_{USj1997}} * PPP_{ij1997}$$

where *VA_P* is the *VA* deflator. A 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* (the drawback is that we don't adjust the capital stock for possible price changes in the benchmark country).

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.

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

(C3) $$\Delta \ln \widetilde{TFP}_{ijt} = \Delta \ln \widetilde{GO}_{ijt} - \overline{\alpha}_{ij} \Delta \ln \widetilde{L}_{ijt} - \overline{\beta}_{ij} \Delta \ln \widetilde{I}_{ijt} - [1 - (\overline{\alpha}_{ij} + \overline{\beta}_{ij})] \Delta \ln \widetilde{K}_{ijt}$$

where $\widetilde{GO}$ denote a gross output index, $\widetilde{L}$, $\widetilde{I}$, and $\widetilde{K}$ are labor services, intermediate input and capital services indices, respectively, and $\overline{\alpha}$ and $\overline{\beta}$ are the average inputs shares over two periods computed as following:

(C4) $$\overline{\alpha}_{ij} = 0.5(\alpha_{ijt} + \alpha_{ijt-1})$$

(C5) $$\overline{\beta}_{ij} = 0.5(\beta_{ijt} + \beta_{ijt-1})$$

Similarly, we define the "raw" *TFP* growth indicator, using the output and inputs variables as defined in (C1).

We also need to address an issue of sectoral aggregation in our data. The breakdown of the 28 subsectors of the EU KLEMS dataset differs from the nine sectors *PACE* classification that we use. We therefore need to merge some of the sub-sectors to conform to the required classification. We collapse "Chemicals and chemical products" and "Rubber and plastic products" in the sector 6. As well, we collapse "Machinery and equipment", "Electrical and optical equipment", "Transport equipment" and "Manufacturing nec; 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 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 used a Tornqvist quantity index (as suggested by O‘Mahony and Timmer, 2009). Unfortunately, we cannot adjust the indices for the inconsistency between quality-adjusted *TFP* and *PACE* measures in sectors 8 and 9 classification, so we should keep it in mind the minor difference in the sectoral breakdown when using quality-adjusted TFP growth measure in our analysis.

Table1: 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

Table 2: Summary Statistics (1997-2009)

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
Adj.TFPG		0.01	0.02	-0.25	0.10
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	8 119	4600	48000
EI	TOE/ bln.euro	1.16	2.49	0.02	42.41

Source: our own computations based on the EUROSTAT, the EUKLEM, the OECD STAN, the OECD ANBERD and the WIOD datasets

Table 3: Summary Statistics of the Main Variables by Country (1997-2009)

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

Source: our own computations based on the EUROSTAT, the EUKLEM, the OECD STAN, the OECD ANBERD and the WIOD dataset

Table 4: Summary Statistics of the Main Variables by Sector (1997-2009)

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

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

Table 5: Weak PH - R&D FE Regression Results

	(1)	(2)	(3)	(4)
PACE	0,043	0,033	-	-
	(0,04)	(0,04)		
PACE(-1)	-	-	-0,021	-0,045
			(0,04)	(0,04)
VA(-1)	0,042	0,013	0,084	0,031
	(0,04)	(0,06)	(0,08)	(0,13)
GOVR&D(-1)	0,043	0.311**	-0,076	0,132
	(0,18)	(0,14)	(0,19)	(0,17)
KR&D(-1)	-	0.654***	-	0.633***
		(0,21)		(0,19)
EXP(-1)	-	0.434*	-	0.519***
		(0,22)		(0,18)
IMP(-1)	-	-0,32	-	-0.633*
		(0,22)		(0,35)
DR(-1)	-	1.806**	-	1.938***
		(0,79)		(0,68)
BR(-1)	-	-1,064	-	-0,898
		(0,82)		(0,70)
F-test	1.32*	5.61***	1.45**	8.46***
Within R-squared	0,05	0,22	0,05	0,26
N. Observations	750	515	694	512
N. Country-sector Effects	129	105	129	104

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; 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 6: Weak PH - Patents FE Regression Results

	(1)	(2)	(3)	(4)
PACE(-1)	0.086***	0.030**	-	-
	(0,02)	(0,02)		
PACE(-2)	-	-	0.096***	0,002
			(0,03)	(0,02)
VA(-1)	0,061	-0,045	-0,032	-0,045
	(0,05)	(0,03)	(0,04)	(0,03)
GOVR&D(-1)	0.323***	-0,073	0.286***	-0,086
	(0,10)	(0,07)	(0,11)	(0,08)
KPAT(-1)	-	0.509***	-	0.487***
		(0,08)		(0,09)
EXP(-1)	-	0,05	-	0,105
		(0,07)		(0,09)
IMP(-1)	-	-0.277**	-	-0.385***
		(0,11)		(0,15)
DR(-1)	-	0,024	-	0,129
		(0,21)		(0,26)
BR(-1)	-	0.275*	-	0.483*
		(0,16)		(0,29)
F-test	6.89***	6.40***	10.32***	6.70***
Within R-squared	0,37	0,39	0,39	0,35
N. Observations	913	639	883	587
N. Country-sector Effects	153	125	151	126

Notes to the table: see Table 5.

Table 7: 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***	-	-	-	-
	(0,06)	(0,07)	(0,07)	(0,07)				
$PACE/VA_{-j}(-1)$	-	-	-	-	0.395***	0.414***	0.374***	0.360***
					(0,09)	(0,09)	(0,10)	(0,10)
$PACE/VA_{-j}*EI_{pre}$	-	-0.074**	-	-0.244**	-	-	-	-
		(0,04)		(0,11)				
$PACE/VA_{-j}*EI_{pre}(-1)$	-	-	-	-	-	-0.122*	-	-0.334**
						(0,07)		(0,15)
VA(-1)	0.105**	0.176*	0.089**	0.171*	0,106	0,119	0,112	0,103
	(0,05)	(0,10)	(0,04)	(0,09)	(0,08)	(0,09)	(0,08)	(0,09)
GOVR&D(-1)	-0.325*	-0.354**	-0,281	-0,294	-0.356*	-0.351*	-0.387*	-0,371
	(0,17)	(0,17)	(0,19)	(0,20)	(0,20)	(0,20)	(0,23)	(0,23)
KR&D(-1)	-	-	0.244*	0,226	-	-	0,171	0,217
			(0,14)	(0,15)			(0,18)	(0,18)
EXP(-1)	-	-	0,025	-0,01	-	-	-0,118	-0,107
			(0,16)	(0,18)			(0,17)	(0,18)
IMP)(-1)	-	-	-0,068	-0,207	-	-	-0,298	-0,24
			(0,27)	(0,28)			(0,34)	(0,34)
DR(-1)	-	-	-0,286	-0,45	-	-	-2.392***	-2.448***
			(0,53)	(0,51)			(0,88)	(0,86)
BR(-1)	-	-	-0,291	0,036	-	-	1.536*	1.584*
			(0,66)	(0,66)			(0,89)	(0,89)
F-statistics	5,65	8,319	4.95***	7.73***	12,985	12,687	14.08***	14.53***
Within R-square	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-squared	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 Chi2 (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
N. Observations	693	629	498	480	654	620	509	492
N. Country-sector Effects	127	120	108	102	124	117	104	98

Table 8: Weak PH - Patents IV Regression - First Stage Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PACE/V A_{-j}(-1)	0.413***	0.458***	0.689***	0.673***	-	-	-	-
	(0,07)	(0,07)	(0,07)	(0,06)				
PACE/VA_{-j}(-2)	-	-	-	-	0.443***	0.448***	0.575***	0.486***
					-0,07	-0,07	(0,08)	(0,08)
PACE/VA_{-j} *EI_{pre}(-1)	-	0.093***	-	-0.166*	-	-	-	-
		(0,03)		(0,10)				
PACE/VA_{-j} *EI_{pre}(-2)	-	-	-	-	-	-0.128**	-	0.547***
						-0,06		(0,16)
VA(-1)	0.171**	0.189**	0.180*	0.176*	0,093	0,106	0.404***	0.439***
	(0,09)	(0,09)	(0,09)	(0,10)	-0,06	-0,07	(0,14)	(0,13)
GOVR&D(-1)	-0,186	-0,198	-0,292	-0,277	-0,105	-0,091	-0,198	-0,221
	(0,16)	(0,17)	(0,21)	(0,22)	-0,18	-0,18	(0,19)	(0,18)
KPAT(-1)			0.378**	0.390**			0.406*	0.415*
			(0,18)	(0,18)			(0,22)	(0,22)
EXP(-1)			0.467***	-0.468**			-0.351*	-0,289
			(0,18)	(0,18)			(0,21)	(0,21)
IMP(-1)			0,486	0,491			0.888**	0.847**
			(0,30)	(0,31)			(0,38)	(0,35)
DR(-1)			-0,637	-0,646			-0.765*	-0.901**
			(0,49)	(0,50)			(0,45)	(0,42)
BR(-1)			0,427	0,467			-0,062	0,204
			(0,43)	(0,42)			(0,48)	(0,40)
F-statistics	16,27	16,646	10.76***	11.00***	7,662	8,179	8.67***	9.10***
Within R-square	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-squared	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 Chi2 (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
N. Observations	862	822	637	620	817	784	573	550
N.Country-sector Effects	150	143	129	123	148	141	119	113

Table 9: 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	-	-	-	-
	(0,20)	(0,14)	(0,32)	(0,20)				
PACE-inst(-1)	-	-	-	-	-0,086	-0,134	-0.403**	0.475***
					(0,11)	(0,10)	(0,17)	(0,18)
VA(-1)	0.100*	0,05	0.123**	0,093	0,086	0,079	0,156	0.190**
	(0,05)	(0,07)	(0,06)	(0,10)	(0,07)	(0,07)	(0,10)	(0,10)
GOVR&D(-1)	-0,20	-0,16	-0,04	0,034	-0,244	-0,26	-0,086	-0,077
	(0,19)	(0,17)	(0,21)	(0,15)	(0,15)	(0,16)	(0,18)	(0,20)
KR&D(-1)	-	-	0.674***	0.563***	-	-	0.665***	0.693***
			(0,19)	(0,19)			(0,16)	(0,15)
EXP(-1)	-	-	0.413**	0.397**	-	-	0.348**	0.291**
			(0,16)	(0,17)			(0,14)	(0,15)
IMP(-1)	-	-	-0,161	-0,168	-	-	-0.494***	-0.500***
			(0,22)	(0,25)			(0,17)	(0,19)
DR(-1)	-	-	1,589	-0,337	-	-	-0,228	-0,438
			(9,12)	(1,98)			(0,68)	(0,72)
BR(-1)	-	-	0,848	-0,372	-	-	0,141	0,254
			(8,52)	(0,90)			(0,49)	(0,51)
N. Observations	693	629	498	480	654	620	509	492
N.Country-sector	127	120	108	102	124	117	104	98

Table 10: 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**	-	-	-	-
	(0.07)	(0.06)	(0,03)	(0,03)				
PACE-inst(-2)	-	-	-	-	0.192***	0.170***	-0.060*	-0.052*
					(0.05)	(0.05)	(0,03)	(0,03)
VA(-1)	0.036	0.039	-0,052	-0,051	-0.059**	-0.056*	-0,008	-0,01
	(0.04)	(0.04)	(0,03)	(0,03)	(0.03)	(0.03)	(0,04)	(0,04)
GOVR&D(-1)	0.308***	0.333***	-0,073	-0,082	0.212**	0.202**	-0.156**	-0.112*
	(0.09)	(0.08)	(0,06)	(0,06)	(0.09)	(0.09)	(0,07)	(0,06)
KR&D(-1)	-	-	0.528***	0.535***	-	-	0.537***	0.518***
			(0,07)	(0,07)			(0,09)	(0,08)
EXP(-1)	-	-	0,079	0,062	-	-	0,083	0,07
			(0,06)	(0,06)			(0,09)	(0,09)
IMP(-1)	-	-	-0.345***	-0.346***	-	-	-0.365***	-0.418***
			(0,11)	(0,11)			(0,13)	(0,13)
DR(-1)	-	-	-0,028	-0,036	-	-	0,108	-0,052
			(0,16)	(0,15)			(0,23)	(0,18)
BR(-1)	-	-	0.291*	0.307*	-	-	0,397	0.580**
			(0,17)	(0,17)			(0,26)	(0,26)
N. Observations	862	822	609	592	817	784	546	523
N.Country-sector	150	143	122	116	148	141	112	106

Table 11: Strong PH - TFP FE Regression

	TFP Level		TFP Growth	
	(1)	(2)	(3)	(4)
PACE(-1)	-0,007	-	0,004	-
	(0,01)		0,00	
PACE(-2)	-	-0,001	-	0,001
		(0,01)		0,00
TFPG-frontier			0.232**	0.226**
			(0,11)	(0,11)
TFP-gap(-1)			-0.078***	-0.071**
			(0,03)	(0,03)
VA(-1)	-0,012	-0,017	0,003	0,008
	(0,02)	(0,03)	(0,01)	(0,01)
IMP(-1)	-0,019	-0,047	-0,02	0,006
	(0,07)	(0,07)	(0,03)	(0,03)
EXP(-1)	-0,006	-0,016	0,04	0,035
	(0,06)	(0,06)	(0,03)	(0,02)
DR(-1)	0,035	0.146*	0,039	0.087***
	(0,04)	(0,09)	(0,04)	(0,03)
BR(-1)	-0,027	-0,15	-0,064	-0,052
	(0,09)	(0,11)	(0,05)	(0,05)
F	5.38***	6.03***	2.85***	6.65***
R-squared	0,21	0,17	0,16	0,18
N. Observations	476	432	476	432
N. Country-sector Effects	95	95	95	

Table 12: Strong PH - TFP Regression - Two-stage Model

	TFP Level		TFP Growth	
	(1)	(2)	(5)	(6)
R&D-pred(-1)	-0,068	-	-0,001	-
	(0,06)		0,00	
PAT-pred(-1)	-	-0.078*	-	0
		(0,04)		0,00
TFPG-frontier	-	-	0,179	0.210**
			(0,11)	(0,10)
TFP-gap(-1)	-	-	0.020***	0,007
			(0,01)	(0,01)
VA(-1)	-0,055	-0,018	-	-
	(0,04)	(0,03)		
IMP(-1)	-0,032	-0,087	-0.008***	-0,005
	(0,12)	(0,08)	0,00	0,00
EXP(-1)	-0,03	-0,043	0.006**	0,003
	(0,07)	(0,06)	0,00	0,00
DR(-1)	0,328	0,167	-0,023	0,058
	(0,25)	(0,24)	(0,08)	(0,06)
BR(-1)	-0.378*	0,115	-0,003	-0,042
	(0,21)	(0,22)	(0,09)	(0,07)
R-squared	0,23	0,2	0,16	0,18
N. Observations	296	354	296	354
N.Country-sector Effects	84	86	84	86

Table 13: Strong PH - TFP IV Regression - First Stage Results

	TFP level				TFP growth	
	(1)	(2)	(3)	(4)	(9)	(10)
PACE/VA$_{-j}$(-1)	0.683***	0.580***	-	-	0.677***	0.560***
	(0,08)	(0,09)			(0,08)	(0,09)
PACE/VA$_{-j}$ *EI$_{pre}$(-1)	-	-0.508***	-	-	-	-0.564***
		(0,19)				(0,18)
PACE/VA$_{-j}$(-2)	-	-	0.616***	0.509***	-	-
			(0,08)	(0,10)		
PACE/VA$_{-j}$ *EI$_{pre}$(-2)	-	-	-	-0.501**	-	-
				(0,21)		
VA(-1)	0.339**	0.447***	0.397*	0.452**	0.333**	0.456***
	(0,13)	(0,14)	(0,20)	(0,18)	(0,14)	(0,15)
IMP(-1)	0.707**	0.793***	0.867***	0.868***	0.633**	0.697**
	(0,28)	(0,27)	(0,33)	(0,31)	(0,28)	(0,28)
EXP(-1)	-0.904***	-0.852***	-0,406	-0,43	-0.890***	-0.817***
	(0,27)	(0,26)	(0,36)	(0,35)	(0,27)	(0,26)
DR(-1)	-1,106	-1,075	-1.202***	-1.241***	-1,038	-1
	(0,88)	(0,88)	(0,28)	(0,30)	(0,89)	(0,89)
BR(-1)	1,308	1,293	1.322**	1.244**	1,301	1,298
	(1,16)	(1,16)	(0,53)	(0,54)	(1,14)	(1,13)
F-statistics	11.36***	13.04***	16.72***	16.03***	10.97***	11.83***
Adjusted R-square	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-squared	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 chi-sq test	0,04	0,12	0,27	0,3	0,64	0,74
P value J-statistic		0,28		0,21		0,51
N. Observations	467	467	413	413	467	467
N. Country-sector Effects	86	86	76	76	86	86

Table 14: 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
	(0,01)	(0,01)			(0,01)	(0,01)
PACE-inst(-2)	-	-	-0,013	-0,005	-	-
			(0,01)	(0,01)		
TFPG-frontier	-	-	-	-	0.241**	0.245***
					(0,10)	(0,09)
TFP-gap(-1)	-0,007	-0,008	-0,012	-0,019	0,007	0,007
	(0,02)	(0,02)	(0,03)	(0,02)	(0,01)	(0,01)
VA(-1)	-	-	-	-	-0.084***	-0.085***
					(0,03)	(0,03)
IMP(-1)	-0,014	-0,022	-0,041	-0,072	-0,018	-0,017
	(0,06)	(0,06)	(0,06)	(0,06)	(0,03)	(0,03)
EXP(-1)	-0,012	-0,001	-0,02	0,001	0,036	0,035
	(0,05)	(0,05)	(0,05)	(0,05)	(0,03)	(0,02)
DR(-1)	0,027	0,029	0.136*	0.148*	0,035	0,035
	(0,04)	(0,04)	(0,08)	(0,08)	(0,04)	(0,04)
BR(-1)	-0,012	-0,023	-0,13	-0,153	-0,055	-0,054
	(0,08)	(0,08)	(0,10)	(0,10)	(0,05)	(0,05)
N. Observations	467	467	413	413	467	467
N. Country-sector Effects	86	86	76	76	86	86