Environmental and Resource Economics (2019) 73:1315–1355
https://doi.org/10.1007/s10640-018-0300-6

Environmental Policy, Innovation, and Productivity Growth: Controlling the Effects of Regulation and Endogeneity

Erik Hille[1] · Patrick Möbius[1]

Accepted: 26 October 2018 / Published online: 8 November 2018

Abstract
We analyze the environmental regulation-productivity nexus and add to the literature in two main ways. First, shadow prices of energy and industrial energy prices are employed as relative measures of policy stringency. To ensure the robustness of the results, the model is also estimated for five alternative measures that have been applied in prior research. Second, we address the endogeneity of environmental regulation, innovation, and trade openness. A cross-country multi-sectoral dataset is utilized, including newly industrialized countries and former transition economies. The estimates show that the positive effects of increases in environmental policy stringency on productivity, which have often been reported in the more recent studies, change to mainly insignificant effects once simultaneity is controlled for. Hence, no support for the strong Porter Hypothesis can be found. Instead, stricter environmental regulation fosters innovation and, therefore, has an indirect, yet not decisive, positive effect on productivity growth.

Keywords Environmental regulation · Productivity growth · Innovation · Shadow prices · Energy prices · Endogeneity

1 Introduction

For several years, researchers have debated the nature of the environmental policy-competitiveness relationship. Many argue that there is a tradeoff between firm or sectoral competitiveness and environmental protection (Dechezleprêtre and Sato 2017; Jaffe et al. 1995). Despite improving the environment, stricter environmental policies may imply additional costs for pollution abatement, alter investment decisions, and restrict inputs in the production process as well as the set of available technologies (Ambec et al. 2013). Consequently, at least in the short run, higher compliance costs may decrease international competitiveness, such as by reducing productivity growth.

✉ Erik Hille
Erik.Hille@hhl.de

Patrick Möbius
Patrick.Moebius@hhl.de

1 HHL Leipzig Graduate School of Management, Jahnallee 59, 04109 Leipzig, Germany

Contrary to the conventional view, some researchers argue that well-crafted environmental regulations can improve firm or sector competitiveness along with environmental quality, by promoting product innovation and efficiency improvements in the production process (Porter 1991; Porter and van der Linde 1995). While this Porter Hypothesis (PH) has often been criticized for its incompatibility with the assumption of profit-maximizing firms (Palmer et al. 1995), more recent lines of theoretical research relying on organizational and market failures, as well as behavioral arguments, show that the hypothesis can be valid (Aghion et al. 1997; Ambec and Barla 2002; André et al. 2009). For instance, in the case of spillovers in the innovation and technology adoption process, a stricter environmental policy can increase firms' productivity by internalizing the positive externalities (Greaker 2006; Mohr 2002).

In general three versions of the PH predict the environmental regulation-competitiveness nexus, namely the weak, strong, and narrow versions (Jaffe and Palmer 1997). This paper focuses on productivity as a measure of competitiveness.[1] In this context, the weak version hypothesizes that regulation induces innovation, which in turn stimulates productivity. However, the overall level of productivity is not improved, because the opportunity costs of additional innovation offset the productivity gains.[2] By contrast, the strong version proposes that increases in environmental regulation raise the overall productivity by facilitating product and process innovation. In this regard, the paper interprets the strong PH in line with the argumentations of Jaffe and Palmer (1997) and Rubashkina et al. (2015). According to the narrow version, market-based instruments, such as taxes or tradable permits, are more likely to induce innovation and productivity growth than command-and-control instruments.

While Dechezleprêtre and Sato (2017) provide a general overview of research on the impact of environmental regulation on competitiveness, Koźluk and Zipperer (2014) review the empirical findings of the impact on productivity growth and the link to innovation. Even though there is ample empirical evidence that well-designed environmental policy tends to bring about positive effects on innovation (Brunnermeier and Cohen 2003; Carrión-Flores and Innes 2010; Lanoie et al. 2011), the impact on productivity remains ambiguous (Brännlund and Lundgren 2009; Cohen and Tubb 2018). Mainly the more recent studies tend to find clearer support for the strong PH (Ambec et al. 2013; Franco and Marin 2017; Yang et al. 2012).

This paper analyzes the effects of environmental regulation on multifactor productivity (MFP) growth, in order to test the strong PH, and contributes to the mixed evidence in primarily two ways. This is the first study on the PH using shadow prices to measure environmental policy stringency. An internationally comparable and accurate measure of policy stringency is central to testing the PH in a multi-country setting. However, heterogeneous policy mixes varying across countries and missing disaggregated data on the sectoral or firm level complicate the measurement (Brunel and Levinson 2016; Dechezleprêtre and Sato 2017). Consequently, despite the large number of applied measurement approaches, there is a need for studies on the environmental regulation-competitiveness nexus to employ sound relative policy stringency measures (Albrizio et al. 2017; Copeland 2011). In this context, shadow prices are often regarded as the preferred measure, which has not yet been used due to data restrictions (Jaffe et al. 2002; Kneller and Manderson 2012). To ensure the robustness of the

[1] Besides productivity, studies have analyzed the effects of environmental regulation on several other measures of competitiveness. These include the impacts on business performance, trade flows, FDI, and employment (Cagatay and Mihci 2006; Lanoie et al. 2011; Millimet and Roy 2016; Walker 2013).

[2] While most empirical research on the weak PH analyzes the environmental regulation-innovation nexus only, a few studies also test the implied link to firms' economic performance, e.g. Lanoie et al. (2011). Similarly, Jaffe and Palmer (1997) interpret the weak version as the extent to which policy stringency stimulates innovation, which, however, implies that the additional innovations do not raise potential profits.

results, industrial energy prices are determined as a second cost-based measure. Furthermore, the estimates are compared to those of five alternative regulatory measures that have been applied in prior research. Second, to control for the effects of endogeneity, the models are estimated using both a fixed effects (FE) and a dynamic panel generalized method of moments (GMM) estimator. Most prior studies do not sufficiently address the potential endogeneity of several explanatory variables of productivity. However, this may bias the estimates. For instance, Cohen and Tubb (2018) find, in a meta-analysis, that studies are more likely to yield evidence supporting the strong PH when an instrumental variable is implemented for environmental regulation. As endogeneity concerns relate not only to environmental regulation and innovation, but also to trade openness (Crepon et al. 1998; Rubashkina et al. 2015; Topalova and Khandelwal 2011), these measures are treated as endogenous.

The analysis utilizes panel data on 14 manufacturing sectors across 28 OECD countries, including non-highly developed economies such as newly industrialized countries and former transition economies from Eastern Europe. Hence, compared to previous research, the paper slightly extends the country coverage and accounts for heterogeneity across countries and sectors in the same and in different development stages.

Positive and significant overall effects of environmental regulation on productivity growth are estimated when the models do not account for simultaneity and utilize the shadow prices of energy as the measure of regulatory stringency. However, after controlling for simultaneity, the impact changes to significantly negative coefficients in the base models, and insignificant coefficients once the models include innovation measures. Thus, no convincing support for the strong PH can be found. Not only are the results highly robust when energy prices are used instead of the shadow prices, but a similar change of the coefficient estimates can also be observed for most of the alternative measures. This evidence is contrary to the results from the more recent studies that increasingly find support for the strong PH. Yet, given that these studies still often do not or only partly address simultaneity issues, it highlights the importance of controlling for endogenous regressors in order to avoid potentially biased estimates. Unlike the overall regulatory effect, innovation efforts along with technological catch-up and pass-through are found to be important drivers of sectoral productivity growth. As environmental policy stringency is positively related to the innovation measures, i.e. with triadic patent counts, firm R&D expenditures, and high-skill labor compensation, the estimates indicate rather that the weak PH is valid. In other words, more stringent environmental regulation induces innovation and, therefore, has an indirect, yet not decisive, positive effect on productivity growth.

The remainder of this paper is organized as follows. Section 2 provides a literature review that concentrates on the sectoral level research. Section 3 details the methodology and data used, by consecutively elaborating on the key variables, descriptive statistics, empirical model, and panel dataset. The estimation results are presented and discussed in Sect. 4 for both the two cost-based and the five alternative measures. Section 5 concludes.

2 Literature Review

The strong version of the PH has been tested at different levels of aggregation, namely at the country, regional, sectoral or firm level, using varying measures for environmental policy, productivity growth, and innovation. A review of the comprehensive work on the environmental policy-productivity nexus is, for example, provided by Dechezleprêtre and Sato (2017) and Koźluk and Zipperer (2014). While the empirical evidence remains ambiguous, the more recent studies tend to find clearer support for the strong PH (Ambec et al. 2013; Brännlund and Lundgren 2009). Cohen and Tubb (2018) carry out a meta-analysis of 103 studies, which reveals that it is more likely to find a positive relationship between environmental regulation and productivity at the more aggregated country or regional level than at the sectoral and firm level, and when an instrumental variable is implemented for environmental regulation. However, given that Young (2018) finds instrumental variable estimates to be generally more often falsely significant and sensitive to outliers, the results of the studies using instruments should be interpreted with caution.

Given that this paper utilizes sector-specific panel data, the focus of the remaining literature review lies on empirical studies at the sectoral level. Table 1 provides an overview of these studies, revealing that the results are also mixed. Early studies testing the impact of environmental regulation on productivity growth find negative effects (Gray 1987; Barbera and McConnell 1990; Dufour et al. 1998). However, these studies either do not control for fixed effects or use relatively small and restricted samples (Koźluk and Zipperer 2014).

Later sectoral studies find heterogeneous results with growing evidence to support the strong PH. Alpay et al. (2002) examine the Mexican and US food processing industry and proxy environmental policy stringency using pollution-abatement costs and expenditures (PACE) for the USA and the number of plant inspections for Mexico. While productivity is found to increase with stricter environmental regulation in the Mexican food industry, no significant effects are revealed for the US industry. Lanoie et al. (2008) determine the ratio of investments in pollution-control equipment to total input costs, so as to measure environmental regulation and lag the variable up to 3 years. Even though a negative contemporaneous effect is estimated for the Canadian manufacturing sectors, positive impacts on productivity growth are found for the second and third year lags. Hamamoto (2006) and Yang et al. (2012) analyze non-North American data, namely Japanese and Taiwanese manufacturing sectors respectively. While the former provides evidence of an indirect positive impact of increases in pollution control expenditures on productivity growth through higher R&D expenditures, the latter find direct support for the strong PH.

More recent studies of the policy-productivity relationship increasingly extend the analysis to a cross-country, multi-sectoral setting. Rubashkina et al. (2015) utilize PACE data for nine manufacturing sectors in 17 European countries, excluding large economies like France, Germany, and Italy. After controlling for potential endogeneity of environmental regulation, they find no significant effect and, thus, no evidence for the strong version of the PH. Franco and Marin (2017) as well as Albrizio et al. (2017) find contrary impacts. Both estimate positive effects using manufacturing data for eight European economies and 17 highly developed OECD countries respectively.[3]

Besides the mixed empirical evidence and increasing support for the strong PH in more recent studies, Table 1 reveals two insights in particular. First, the applied measures of environmental policy stringency differ across the studies, ranging from ad-hoc weighted indexes, to environmentally related taxes, to survey-based cost data. Thereby, the majority of research utilizes PACE data or other survey-based cost measures and few studies perform robustness checks with alternative policy measures. However, the PACE data and many of the other commonly used measures face conceptual problems and may be biased (Brunel and Levinson 2016; Dechezleprêtre and Sato 2017).[4] Second, many studies do not control for endogeneity

[3] It should be noted that Albrizio et al. (2017) analyze both sectoral and firm-level data. Even though no evidence is found for the strong PH at the firm level, positive effects on productivity growth are estimated at the sectoral level.

[4] Section 3.2 introduces the applied shadow prices and energy prices and provides a more detailed discussion of the employed alternative measures.

Table 1 Overview of sector-specific empirical studies on the environmental regulation-productivity nexus

Study	Measures		Endog.	Sample		Results
	Prod.	Environmental policy stringency		Country (# of countries)	Sectors (# of sectors)	
Gray (1987)	MFP growth	Pollution abatement costs and expenditures	No	USA (1)	Manufacturing sectors (450)	Negative effect on MFP growth
Barbera and McConnell (1990)	MFP growth	Required abatement capital	No	USA (1)	Manufacturing sectors (5)	Negative direct effect on MFP growth
Dufour et al. (1998)	MFP growth	Investments in pollution-control equipment to total cost	Partly[a]	Canada (1)	Manufacturing sectors (19)	Negative effect on MFP growth
Alpay et al. (2002)	MFP growth	Number of plant inspections (MEX), pollution abatement costs (USA)	No	USA, Mexico (2)	Food manufacturing sectors (1)	Positive effect on MFP growth for MEX, no effect on MFP growth for USA
Hamamoto (2006)	MFP growth	Pollution control expenditures	No	Japan (1)	Manufacturing sectors (5)	Indirect positive effect on MFP growth via increasing R&D expenditures
Lanoie et al. (2008)	MFP growth	Investments in pollution-control to total cost	No	Canada (1)	Manufacturing sectors (17)	Negative contemporaneous effect, positive effect in 2nd and 3nd year lag
Yang et al. (2012)	MFP index	Abatement capital, abatement fees	No	Taiwan (1)	Manufacturing sectors (234)	Positive effect on MFP index

Table 1 continued

Study	Measures		Endog.	Sample		Results
	Prod.	Environmental policy stringency		Country (# of countries)	Sectors (# of sectors)	
Rubashkina et al. (2015)	MFP growth/level	Pollution abatement and control expenditures	Partly[b]	Europe (17)	Manufacturing sectors (9)	No effect on MFP growth/level
Albrizio et al. (2017)	MFP growth	Environmental policy stringency index	No[c]	OECD (17)	Manufacturing sectors (10)	Positive short-term effect on MFP growth
Franco and Marin (2017)	MFP index	Environmental taxes	Partly[d]	Europe (8)	Manufacturing sectors (13)	Positive effect on MFP index

Productivity (Prod.); Correct for potential endogeneity of environmental regulation, innovation, and trade openness (Endog.); Number (#)

[a]Dufour et al. (1998) test for the endogeneity of environmental regulation and their control variables. Instruments are then introduced for the endogenous variables. Yet, their final specification does not include a measure for innovation and trade openness

[b]Rubashkina et al. (2015) control for the potential endogeneity of environmental policy stringency. However, they do not account for the potential endogeneity of their innovation and trade openness measures

[c]Albrizio et al. (2017) test whether the used environmental policy stringency index is endogenous and detect that reversed causality is not an issue. While they have not tested for the potential endogeneity of their innovation proxy, a trade openness control variable is not included in their estimations

[d]Franco and Marin (2017) include an instrumented innovation proxy. Yet, they do not test for the potential endogeneity of the environmental tax rates. Franco and Marin (2017) argue that environmental tax rates are exogenously set by the government and, hence, reversed causality is not regarded as an issue. A trade openness control variable is not included in the analysis

of the explanatory variables, which may also bias their estimates. As early as 1987, Gray argues that not only environmental regulation may influence productivity, but also the converse may be true. For instance, industries with low productivity growth may decide to lower their pollution-abatement expenditures to cut costs. Similarly, high-performing industries may encourage the implementation of stricter environmental regulation. Apart from environmental policy stringency, innovation, and trade openness may also be potentially endogenous (Amiti and Konings 2007; Crepon et al. 1998; Lanoie et al. 2011; Topalova and Khandelwal 2011). Yet, while few articles correct for the endogeneity of innovation (Franco and Marin 2017), to the best of the authors' knowledge, no empirical study on the environmental policy-productivity nexus has so far accounted explicitly for the possible endogeneity of trade openness.

3 Methodology and Data

3.1 Productivity Growth Measure

This paper uses MFP growth to quantify productivity growth. Employing an MFP measure to proxy industrial competitiveness is in line with the original concept of Porter (1991) and Porter and van der Linde (1995), as well as with recent empirical studies on the environmental regulation-productivity relationship (Albrizio et al. 2017; Franco and Marin 2017; Rubashkina et al. 2015; Lanoie et al. 2008). The MFP growth rates are calculated using traditional growth accounting (Solow 1957; Jorgenson and Griliches 1967; O'Mahony and Timmer 2009). Specifically, a standard neoclassical production function with Hicks-neutral, disembodied technical progress is utilized to determine a gross output-based measure of MFP growth:

$$Y_{cit} = f_{cit}(K_{cit}, L_{cit}, X_{cit}, T_{cit}) \tag{1}$$

Accordingly, the gross output Y of sector i in country c in year t is a function of the primary inputs of capital K and labor L, the intermediate inputs X, and the level of technology T. Thus, gross output-based measures capture the goods and services produced within a sector, technological progress, changes in product and process efficiency, and capacity utilization. Because intermediate inputs are included in the production function, gross output-based measures are less sensitive to changes in the vertical integration of an industry (Schreyer 2001).

In order to empirically implement the growth accounting framework for stock and discrete time data, the Törnqvist (1936) volume index is commonly applied (Albrizio et al. 2017; O'Mahony and Timmer 2009; Rubashkina et al. 2015)[5]:

$$\begin{aligned} MFP_{cit} = ln[T_{cit}/T_{cit-1}] = ln[Y_{cit}/Y_{cit-1}] - \overline{\vartheta}_{X,cit} * ln[X_{cit}/X_{cit-1}] - \overline{\vartheta}_{K,cit} * \\ ln[K_{cit}/K_{cit-1}] - \overline{\vartheta}_{L,cit} * ln[L_{cit}/L_{cit-1}] \end{aligned} \tag{2}$$

[5] The traditional technique of measuring MFP growth with the help of the Törnqvist (1936) volume index has been furthered during the last few decades, e.g. by Olley and Pakes (1996) and Levinsohn and Petrin (2003). Ackerberg et al. (2015) built on the ideas in both papers and developed a recent alternative estimation approach. Their approach is able to account for the endogeneity of inputs, and solves prior functional dependence problems in order to identify the labor coefficient. The general findings presented in Sect. 4 are robust to changes in the MFP measure. Examples of results using MFP growth rates estimated with the help of the Ackerberg et al. (2015) approach are shown in Table 5 in "Appendix A".

The index measures MFP as the difference between the growth in output and the cost-share-weighted growth in the inputs X, K, and L, using a translogarithmic functional form. Accordingly, the cost-weighted factor shares of the inputs are (O'Mahony and Timmer 2009):

$$\begin{cases} \overline{\vartheta}_{X,cit} = 1/2[P_{X,cit}X_{cit}/Y_{cit} + P_{X,cit-1}X_{cit-1}/Y_{cit-1}] \\ \overline{\vartheta}_{K,cit} = 1/2[P_{K,cit}K_{cit}/Y_{cit} + P_{K,cit-1}K_{cit-1}/Y_{cit-1}] \\ \overline{\vartheta}_{L,cit} = 1/2[P_{L,cit}L_{cit}/Y_{cit} + P_{L,cit-1}L_{cit-1}/Y_{cit-1}] \end{cases}, \ \vartheta_{X,cit} + \vartheta_{K,cit} + \vartheta_{L,cit} = 1 \tag{3}$$

where $P_{X,cit}$, $P_{K,cit}$, and $P_{L,cit}$ represent the costs of the inputs X, K, and L, respectively. Following previous research, this paper approximates the MFP growth rates on the basis of the MFP index, which is determined using Eqs. (2) and (3).

3.2 Environmental Policy Measures

To test the validity of the strong PH concerning positive regulatory effects on productivity growth, a relative measure of environmental policy stringency is needed. This paper uses shadow prices of energy, sectoral energy prices, and five alternative measures of relative policy stringency.

A variety of measures and instruments have been used in prior empirical research to proxy environmental policy stringency. The different approaches are summarized, for example, in Brunel and Levinson (2016) and Millimet and Roy (2016). In general, the measures fall into five categories, i.e. (1) private sector abatement costs, (2) measures based on pollution and energy use, (3) composite indexes, (4) public sector efforts, and (5) direct assessments of individual policies (Brunel and Levinson 2016). Many of the measures face conceptual difficulties ranging from limited international comparability and data availability at the sectoral level, to problems in reflecting the multidimensionality of the implemented policy mix (Brunel and Levinson 2016; Dechezleprêtre and Sato 2017). Compliance cost estimates that are determined with the help of a shadow price approach address these difficulties and are unlike the commonly implemented PACE data non-survey-based.[6] The shadow prices are also not subject to several impeding characteristics of measures from the other four categories: they may not be inherently simultaneous like the pollution and energy use measures; they are not weighted ad-hoc like most environmental regulation indexes; they are internationally comparable unlike public sector expenditures and enforcement; and they are broad enough to reflect the policy mix, unlike assessments based on individual regulations.[7] Therefore, shadow prices are often regarded as the ideal relative measure but have not yet been applied to the environmental policy-productivity nexus given the limited data availability (Jaffe et al. 2002; Kneller and Manderson 2012).

This paper is the first study to use the recently published shadow prices of energy of Althammer and Hille (2016) as the measure of policy stringency to test the strong PH.[8]

[6] The major disadvantage of survey-based compliance cost measures is that the central question, namely how much a factory spent on pollution abatement, has become more difficult to answer for the plant managers. In particular the evaluation of cost shares for product and process modifications that changed in response to environmental regulations many years ago, may no longer be reliable (Brunel and Levinson 2016).

[7] For a detailed discussion of the strengths and weaknesses of the shadow price approach, see e.g. Althammer and Hille (2016) or van Soest et al. (2006).

[8] Althammer and Hille (2016)'s shadow prices of energy are available for a relatively rich sector-specific dataset containing 33 primary, secondary, and tertiary sectors in 28 OECD countries for the period 1995–2009.

Shadow prices have been used in several studies to indirectly measure compliance costs by including a pollutant or an environmental resource as an input or as an output in the technology (Färe et al. 2005; Hille and Shahbaz 2018; Huhtala and Marklund 2008; van Soest et al. 2006). The approach of Althammer and Hille (2016) is closely related to van Soest et al. (2006), who were the first to measure environmental policy stringency on the basis of the shadow prices of energy—an input that is widely used across countries and sectors. In order to determine the shadow prices, Althammer and Hille (2016) estimate sectoral cost functions. They thereby utilize Shephard's lemma and the choices made by the market participants, disclosing information on their profit-maximizing behavior. In this context, the shadow prices are defined as the potential decrease in spending on other variable inputs, which may be achieved by increasing the use of the polluting input of energy, while keeping output constant (van Soest et al. 2006). For example, if the use of energy is weakly regulated in a certain sector of a country, the energy price will be comparatively low and firms will use more energy. Consequently, a low shadow price is an indication of relatively weak policy stringency, and a high shadow price of more stringent regulation.

Shadow prices of energy have been interpreted as a measure of both environmental (Brunel and Levinson 2016; van Soest et al. 2006) and climate policy stringency (Hille 2018; Sato et al. 2015b). Specifically, the shadow prices utilized reflect all direct and indirect environmental policies which have an effect on the price of emission-relevant energies.[9] This includes market-based instruments such as tradable permits and carbon-related input taxes, command-and-control regulations like emission standards, as well as technology restrictions. Yet, the shadow prices may also reflect policies other than environmental ones, namely when those policies influence the price of the polluting input energy (Althammer and Hille 2016). While van Soest et al. (2006) argue that this is an advantageous attribute of the shadow prices when industry location, and consequently also investment decisions are analyzed, this paper tries to control for the characteristic in two ways. First, additional supply- and demand-side policy variables are included in the estimation to capture the effects of government regulations and macroeconomic conditions, which could also alter the use of the polluting input. Second, five alternative, non-cost-based measures of environmental policy stringency are used to ensure that the findings are robust and not a mere consequence of the identification of the shadow prices.

Sector-specific industrial energy prices are estimated as a second cost-based measure for policy stringency, which also addresses the above-mentioned challenges. Energy prices have lately been employed in competitiveness analyses that focus on the trade effects of climate or energy regulation (Aldy and Pizer 2015; Gerlagh et al. 2015; Sato and Dechezleprêtre 2015). The intuition is that energy prices are affected not only by energy policies, but also by market-based carbon instruments, such as emission taxes or cap-and-trade systems, that operate mainly by raising energy prices (Aldy and Pizer 2015). Accordingly, most of variation in industrial energy prices across countries during the time period under consideration can be explained by changes in the tax component, and only in part by wholesale price differences (Sato et al. 2015b). Hence, energy prices reflect private sector energy costs more directly than the shadow prices of energy, and comparatively high energy prices are interpreted as a sign of stricter regulation. The sector-specific energy prices are determined by adapting the methodology of Althammer and Hille (2016). Specifically, a weighted average is calculated

[9] This implies that environmental policies such as waste regulation or water quality standards, that have a limited effect on energy prices, are not or only partly reflected in the shadow prices.

with the help of the industrial energy prices of seven energy carriers, the sector-specific gross energy use of the seven energy carriers, and the total energy price development.[10]

In addition, the empirical model is estimated for five alternative measures of environmental regulation that have been adopted in prior research. These measures are the changes in sulfur oxide (SO_X), nitrogen oxide (NO_X), and carbon dioxide (CO_2) emission intensities, the Environmental Policy Stringency (EPS) index interacted with the sectoral pollution intensity, and the ratio of environmental to total tax revenue. While the shadow and energy prices fall into the first category of abatement cost estimates, the alternative measures belong to the second, third, and fourth categories. Given that this paper tests for international empirical evidence of the PH, alternative measures from the fifth category that directly assess individual regulations are not regarded as suitable, as they cannot reflect the multidimensional policy mix and lack international comparability. Except for the emission-based measures, no high correlations can be detected among the various alternative measures and with the shadow and energy prices.[11] This coincides with the analyses of Althammer and Hille (2016), Brunel and Levinson (2016), and van Soest et al. (2006), who show that different measures of policy stringency are remarkably uncorrelated. In particular, abatement cost estimates are found not to correlate highly with measures from other categories.

Measures based on emissions and energy use utilize the inherent relationship between these indicators and environmental regulation. However, high levels of the measures can be interpreted as both policy stringency and laxity (Barbera and McConnell 1990; Carrión-Flores and Innes 2010; Costantini and Crespi 2008). To avoid this simultaneity, the reduction in emissions are sometimes applied as regulatory stringency measures to analyze the environmental policy-competitiveness nexus (Gollop and Roberts 1983; Javorcik and Wei 2003). In this manner, data on emissions with strong local effects, such as SO_X and NO_X, serves to approximate environmental or air pollution regulation. As CO_2 emissions, which account for roughly two thirds of global greenhouse gas emissions (World Bank 2017a), are targeted in various climate agreements, they are used to measure climate policy stringency. This paper determines the sector-specific changes in the emissions of SO_X, NO_X, and CO_2 per value added as the first three alternative measures. Given that a reduction in the emission intensities is associated with higher regulatory stringency, the indicators are multiplied by minus one, i.e. the final measures are $-\Delta SO_X/VA$, $-\Delta NO_X/VA$, and $-\Delta CO_2/VA$. This ensures that the coefficients of the emission-based measures have the same expected signs as those of the other policy measures.

Composite indexes compress the multidimensional regulatory environment into one, usually country-specific, cardinal number. An overview of the large number of country-level performance indexes is provided by Bandura (2008). Even though composite indexes aim to be comprehensive indicators of policy stringency, in particular the methodology of the index formation is subject to criticism. Specifically, the weighting and normalization of the indexes are often highly arbitrary and the scientific aggregation rules, which ensure the indicator's consistency and meaningfulness, are frequently not taken into account (Böhringer and Jochem 2007). In addition, the scales of composite indexes may be difficult to interpret, and survey-based indexes may be potentially biased (Althammer and Hille 2016). In the context of competitiveness, both Cagatay and Mihci (2006) and recently Albrizio et al. (2017) employ environmental regulation indexes based on frameworks developed by the OECD. Following Albrizio et al. (2017), the country-level EPS index is interacted with the pre-sample sectoral

[10] The energy price estimation is based on the following seven energy carriers: coal, natural gas, gasoline, diesel, heavy fuel oil, light fuel oil, and electricity.

[11] The authors are happy to provide the correlation coefficients upon request.

pollution intensity to compute the fourth alternative measure.[12] The pollution intensity is thereby approximated using gross energy use per value added. While higher values of the EPS index that ranges from 0 to 6 are interpreted as more stringent environmental regulation, the interaction with the pollution intensity is intended to scale the indicator down to the sectoral level.

Moreover, studies on the strong PH sometimes employ measures based on public sector expenditures and enforcement efforts related to the environment. For instance, Alpay et al. (2002) and Franco and Marin (2017) respectively apply the number of plant inspections and environmental tax intensities. While reflecting enforcement, an important dimension of policy stringency, public sector environmental efforts are, in part, unsuitable as regulatory measures for international studies (Althammer and Hille 2016). For example, measures based on the size of the administrative body in environmental agencies are difficult to compare internationally. Likewise, some public sector expenditures, such as tax incentives, may reduce private sector costs, thus requiring a careful interpretation of policy stringency and laxity, depending on the policy in question (Brunel and Levinson 2016). As the fifth alternative measure, the national share of environmental tax revenue in total tax revenue is taken from the OECD (2017). In general, a high share of environmental taxes is an indication of stringent environmental regulation. van Soest et al. (2006) note however, that this may also apply to a low share, when environmental taxes have eroded the tax base.

3.3 Innovation Measures

Unlike environmental regulation, innovation is widely acknowledged as a strong driver of productivity growth. Most studies testing the PH use data on patents (Brunnermeier and Cohen 2003; Jaffe and Palmer 1997; Rubashkina et al. 2015) or R&D expenditure (Hamamoto 2006; Kneller and Manderson 2012; Yang et al. 2012) to proxy innovation efforts. Besides the number of triadic patents and firm R&D expenditure, this paper also utilizes data on high-skill labor compensation. While patents represent an intermediate-step measure of innovation indicating successful research, the other two measures are upstream inputs in the inventive process.[13]

Given that patent data is closely linked to the number and quality of inventions, patents are often regarded as the preferred innovation measure (Franco and Marin 2017; Griliches 1990). Yet, patent-based measures face several methodological challenges, including heterogeneous patent laws across countries that are subject to change over time, a varying propensity to file patent applications across different technical fields, and a skewed value distribution of filed patents for economic processes (Dernis and Guellec 2002; Haščič et al. 2015; OECD 2009). These may be reasons for the limited geographical scope of studies that utilize sector-specific patent data, focusing, for example, on US (Brunnermeier and Cohen 2003; Jaffe and Palmer 1997) or on European manufacturing sectors (Franco and Marin 2017; Rubashkina et al. 2015).

In order to solve these issues, this paper is, to the best of the authors' knowledge, the first analysis of the PH determining sector-specific triadic patent counts. Triadic patents protect the same invention through a set of corresponding patents filed at the US Patent and Trademark

[12] While the EPS index is available for a comparatively large number of countries over time, the OECD (2017) does not provide data for Estonia, Luxembourg, and Mexico, as well as for Slovenia until 2007.

[13] To ensure that the individual predictors of the three innovation proxies are not biased when they are included jointly in the estimation, the variables are tested for multicollinearity. Neither the simple correlation coefficients nor the variance inflation factors provide any indication of multicollinearity.

Office, the European Patent Office, and the Japan Patent Office. The International Patent Classification thus guarantees a unified technical classification of the filed patents. Given that an international patent protection is accompanied by higher costs and time lags, inventors tend only to extend their patent application if the patent is expected to yield comparatively high returns (Martínez 2011; OECD 2009). Hence, the utilization of triadic patents improves international comparability, avoids the double counting of patents, eliminates home bias, and includes primarily high-value patents (Dernis and Guellec 2002; Martínez 2011). The patent counts are assigned to a respective country and year, in accordance with the inventor's place of residence and the date of the first patent application. To allocate the patents from the technology classification to the manufacturing sectors, the concordance table of van Looy et al. (2015) is applied, which updates the matching algorithm of Schmoch et al. (2003) to changes in the industry classification.

In addition to the triadic patents, R&D expenditures and the high-skill labor compensation represent complementary innovation measures. R&D expenditures are a necessary condition for financing the R&D process which is intended to create inventions. Through implementing the inventions in economic processes, R&D expenditures may indirectly stimulate productivity growth. The used data on firm R&D expenditures identifies the corporate innovation efforts by capturing the funding of the three main types of R&D activity, i.e. basic research, applied research, and experimental development (OECD 2015). As the firm R&D expenditures are not available for the full set of analyzed countries, the compensation of highly-skilled labor is included as an additional innovation measure, which partly captures the same dimensions of innovation.[14] The measure denotes the importance of a well-educated workforce for corporate innovation.

3.4 Descriptive Statistics of Key Variables

This section briefly analyzes the characteristics of the key variables. Table 6 in "Appendix B" provides an overview of the country and sector median values for MFP growth, the lagged two-period moving average of the shadow prices of energy, the number of triadic patents per value added, and the firm R&D expenditures per value added.[15]

While the median MFP growth rates are the highest in Germany and Canada, the lowest values can be found for Turkey and Mexico. At the industry level, the electrical and optical equipment sector (ISIC Rev. 30–33) experienced the highest MFP growth, as opposed to the coke, refined petroleum, and nuclear fuel sector (ISIC Rev. 23) with the lowest growth rates. Interestingly, the electrical and optical equipment sector is also the one with the highest median patent activity and corporate investments in R&D, as well as the strictest environmental regulation. Similarly, the coke, refined petroleum, and nuclear fuel sector is among the sectors with the lowest number of filed triadic patents, has below-average firm R&D expenditures, and faced the second lowest median shadow price of energy.

[14] The OECD (2017) does not provide data on firm R&D expenditures for Belgium, Ireland, Luxembourg, and the Netherlands. In addition, the R&D expenditure data includes a smaller number of missing values at the sectoral level. These are estimated following the methodology of Erumban et al. (2012) when setting up the World Input-Output Database (2012c). Specifically, the country-specific growth rates for the total manufacturing sector are adapted to the individual manufacturing sectors. The remaining missing values are estimated with the help of linear interpolation and backward extrapolation.

[15] The dataset used, which includes information on 14 manufacturing sectors in 28 OECD countries between 1995 and 2009, is introduced in Sect. 3.6. Similar patterns can be observed for the energy prices and the high-skill labor compensation per value added.

At the country level, this first observation only seems to hold for the innovation-productivity nexus, but not for the environmental policy-productivity nexus. For instance, Turkey and Mexico, the countries with the lowest median MFP growth rates, have the lowest median patent activity and corporate R&D expenditure. Yet, their shadow prices are comparatively high.[16]

Sectoral scatter plots of the innovation-productivity and the environmental policy-productivity relationship support this differentiated picture.[17] On the one hand, no relationships and, in part, negative relationships can be found when the MFP growth rates are plotted against the lagged two-period moving averages of the shadow prices. In other words, stricter environmental regulation does not seem to result directly in higher productivity. On the other hand, both the number of triadic patents per value added and the firm R&D expenditures per value added tend to be positively related to MFP growth. Hence, higher innovation activity seems to entail higher MFP growth.

3.5 Empirical Model

The focus of this paper is on the analysis of the relationship between environmental regulation and sectoral productivity growth, while controlling the effects of endogeneity. The empirical model thereby follows the recent literature (Albrizio et al. 2017; Rubashkina et al. 2015) by adopting a technological catch-up and pass-through specification of productivity growth (Acemoglu et al. 2006; Aghion and Howitt 2006):

$$\begin{aligned} MFPGrowth_{cit} &= \alpha_0 + \alpha_1 EnvPolicy_{ciMovAv} + \alpha_2 MFPLeader_{it} + \alpha_3 MFPGap_{cit-1} \\ &\quad + \alpha_n X^n_{cit-1} + \mu_t + \varepsilon_{cit}, \\ \varepsilon_{cit} &= \eta_{ci} + \nu_{cit} \end{aligned} \tag{4}$$

The sector-specific MFP growth in country c, sector i, and year t is a function of environmental policy stringency $EnvPolicy_{ciMovAv}$, the technological frontier $MFPLeader_{it}$, the technological gap $MFPGap_{cit-1}$, and a vector of control variables X^n_{cit-1}. In order to control for time fixed effects, which potentially influence productivity growth across all industries, μ_t is added. ε_{cit} denotes the idiosyncratic error term capturing the unobserved country-sector effects η_{ci} as well as idiosyncratic shocks ν_{cit}.[18]

[16] A detailed discussion of the country level rankings of the shadow prices is given in Althammer and Hille (2016). One explanation for the relatively high shadow prices for economies with below-average incomes in this paper is that the shadow prices are measured in PPP. Hence, after adjusting for international price differences, these countries tend to spend a higher share on energy costs, which include a regulation-induced markup that also increases proportionally through the PPP conversion. In general, measures of regulatory stringency have been made internationally comparably, using both market exchange rates and PPP. Examples of studies that apply the latter methodology include Costantini and Crespi (2008), Sato et al. (2015b), and van Soest et al. (2006). While PPP is regarded as particularly suitable in the context of energy costs when there are specific country price levels, the use of market exchange rates becomes more applicable when input and output markets are internationally integrated (Sato et al. 2015b). Given that this paper utilizes a heterogeneous dataset of countries at partly different development stages and levels of international integration, all monetary values are converted to PPP. Nevertheless, it should be noted that the inclusion of country-sector fixed effects in the regression analysis, as done in this paper, should eliminate any differences between the PPP and the market exchange rate version (Sato et al. 2015b).

[17] For the scatter plots, see the HHL working paper version of this paper.

[18] Besides the time fixed effects and unobserved country-sector fixed effects, the model has been estimated with additional sector fixed effects. The general findings remain unchanged. For corresponding examples of results of the final specification, see columns (39) and (40) in Table 9 in “Appendix C”.

Environmental regulation $EnvPolicy$ is measured using the shadow prices of energy, industrial energy prices, and the five alternative regulatory measures. To account for reverse causality and possible time lags of the regulatory effects (Franco and Marin 2017; Lanoie et al. 2008), the environmental policy stringency variables are included as lagged two-period moving averages.[19] Positive and significant coefficient estimates would support the strong version of the PH.

The rationale of including the technological frontier $MFPLeader$ and the technological gap $MFPGap$ is grounded in standard Neo-Schumpeterian theory (Acemoglu et al. 2006; Aghion and Howitt 2006).[20] On the one hand, productivity growth depends on the technological pass-through, i.e. a firm's or sector's ability to innovate. Technologically advanced firms are expected to have better access to financial resources along with a well-trained human capital stock and managerial capacities suited to innovation. By widening the available set of technologies, the technologically advanced firms may scale up productivity. In that regard, the technological frontier $MFPLeader$ is estimated by the highest MFP level across countries in sector i at time t (Rubashkina et al. 2015; Bas et al. 2016). On the other hand, productivity growth may be achieved through knowledge and innovation spillovers fostering the adoption of more efficient existing technologies. The potential gains from this technological catch-up are expected to be higher for a larger distance to the technological frontier $MFPLeader$, which is captured by the technological gap $MFPGap$. Because the technology and knowledge transfer tend to occur over time, $MFPGap$ is lagged by 1 year (Albrizio et al. 2017; Griffith et al. 2004).

To control for confounding factors, which potentially have an impact on productivity growth, a vector of country- and sector-specific covariates X^n is added to the model. First, the vector includes the three measures of innovation, namely the number of triadic patents, firm R&D expenditures, and the high-skill labor compensation. Besides explaining the direct impact of innovation on productivity growth, the inclusion of the innovation measures helps to filter the indirect effect of environmental regulation via innovation on productivity growth.[21] In order toaccount for differences in sector sizes, the three innovation measures are divided by

[19] Recent empirical studies on the environmental regulation-productivity nexus include the policy stringency variable with different lag structures, i.e. with a 1-year lag (Franco and Marin 2017), a one and 2-year lag (Rubashkina et al. 2015; Yang et al. 2012), or a lagged moving average (Albrizio et al. 2017). A lagged two-period moving average is used instead of a 1-year lag to account for forward-looking responses of firms to new regulations (Albrizio et al. 2017) and for the time needed to initiate R&D activities, discover and adopt new technologies, and observe the effects on productivity (Yang et al. 2012). Alternative lag structures of the shadow and energy prices have been tested, e.g. a 1-year lag, a 2-year lag, or both time lags. Overall, such changes in the lag structures do not significantly alter the results.

[20] Apart from the recent environmental policy-productivity literature (Albrizio et al. 2017; Rubashkina et al. 2015), both a technological frontier and a technological gap variable have been included in productivity specifications in a variety of other fields, including international trade (Bas et al. 2016) and development economics (Bourlès et al. 2013; Griffith et al. 2004). To avoid the results being distorted by over-parameterization, alternative specifications have been estimated. As can be seen in columns (47)–(52) in Table 10 in "Appendix C", the signs and significance levels of the remaining variables are fairly robust to changes in both variables.

[21] There is convincing evidence that environmental regulation induces (environmental) innovation (Brunnermeier and Cohen 2003; Jaffe and Palmer 1997; Lanoie et al. 2011). Table 11 in "Appendix D" shows that this relationship may also be present in this paper. Thus, excluding the innovation measures in Eq. (4) may lead to omitted variable bias, as the potential indirect effect of environmental regulation through innovation on productivity growth cannot be captured. Alternative specifications have been tested, which, however, do not change the detected evidence on the PH. For instance, an interaction effect between innovation and environmental regulation yields the same results as combining the estimations on the regulation-productivity nexus in Table 2 and on the regulation-innovation nexus in Table 11 in "Appendix D".

the sectoral value added. Second, a fixed effect capturing the potential negative impact of the world financial crisis is added to the model. Third, as the participation in international trade can also affect productivity growth, such as through technology transfers or higher innovative pressures induced by international competition, a sector-specific trade openness covariate is included (Grossman and Helpman 2001; Lucas 1988). Specifically, an outcome-based measure of trade openness is implemented by determining the ratio of the sum of each sector's exports and imports to the sectoral output (Hille 2018; Rose 2004). Fourth, the paper adopts two supplementary country-specific supply- and demand-side policy indices. Both variables help to control for the impacts of policies other than environmental policy. Regarding the former, the Regulatory Quality Index of the World Bank's Worldwide Governance Indicators is utilized to capture the government's ability to implement policies that enhance an economy's productive capability (Kaufmann et al. 2010). For the latter, a monetary and fiscal policy index is determined following Delgado et al. (2012). Accordingly, the demand-side policy indicator reflects the importance of macroeconomic stability for productivity growth by incorporating information on inflation, government net debt, as well as the government surplus or deficit.[22] Lastly, energy-intensive sectors are sometimes found to spend more on pollution abatement, independent of sectoral environmental policy stringency (Rubashkina et al. 2015), which may influence productivity growth. For this reason, the sectoral energy intensity is included as a final control variable.

Equation (4) is estimated using a FE and the system GMM estimator (Arellano and Bover 1995; Blundell and Bond 1998). As Eq. (4) includes both time and individual fixed effects, the FE estimator is specified as a two-way FE model employing the Huber-White Sandwich estimator to determine heteroskedasticity-robust standard errors (Huber 1967; White 1980).[23] The results of the FE estimator are used as a benchmark, and are compared to those of the GMM estimator that addresses the potential endogeneity of environmental policy stringency, innovation, and trade openness.[24]

System GMM controls for endogeneity by using the lagged values of the potential endogenous variables as instruments for the transformed equation (Arellano and Bond 1991; Holtz-Eakin et al. 1988) and the lags of their first differences as instruments in the levels Eq. (Arellano and Bover 1995; Blundell and Bond 1998). Specifically, the endogenous variables are used as instruments only if they are also an explanatory variable in the respective specification.[25] Besides addressing the endogeneity of the regressors, the GMM estimator is suitable for panels with many individuals and relatively short time periods, with fixed effects, and with idiosyncratic disturbances that are correlated and heteroskedastic within individuals (Roodman 2009). In order to improve the efficiency of system GMM and to avoid downward biased standard errors, Windmeijer (2005)'s two-step standard error correction is applied.

22 For a detailed discussion of the rationale behind and methodology of the demand-side policy indicator, see Delgado et al. (2012).

23 A robust Hausman test was performed and indicates that the FE estimator is preferable to the random effects estimator. The decision to include time fixed effects in the FE model is validated by the testparm statistic, which shows that the time fixed effects are not jointly equal to zero.

24 In general, the main sources of endogeneity are measurement errors, omitted variables, and simultaneity. The FE estimator controls for omitted variable bias by including fixed effects for unobserved characteristics, but is not capable of accounting for simultaneity. In contrast, the GMM estimator controls for both omitted variable bias and simultaneity between the left- and right-hand side variables.

25 This implies for the four specifications introduced in Sect. 4.1 that in the first specification, the environmental regulation variable is instrumented. In the second specification, environmental regulation and trade openness are used as instruments. Lastly, in the third and fourth specification, environmental regulation, trade openness, and the respective innovation proxies are instrumented.

3.6 Data

The estimation utilizes sector-specific panel data for 14 manufacturing sectors in 28 OECD countries between 1995 and 2009.[26] A detailed overview of the included countries and sectors is given in Table 6 in "Appendix B". Besides highly developed countries, the dataset includes newly-industrialized countries such as Mexico and Turkey, and former transition economies from the Eastern bloc. Hence, the data does, in part, reflect the effects of structural reforms after the fall of the Iron Curtain and the changing determinants that are relevant for productivity growth during a country's development process.

Tables 7 and 8 in "Appendix B" summarize the final set of variables, their units of measurement, and provide the corresponding summary statistics. The largest number of variables is determined with the help of the base variables provided by the World Input-Output Database (2012a, b, c) and the OECD (2017). This includes from the former, the base variables required for the estimation of the MFP variables, as well as the emissions and energy use data used for several environmental regulation measures. Moreover, the World Input-Output Database provides data on the gross output, value added, high-skill labor compensation, trade flows, and sector-specific deflators. The OECD supplements information on patents, R&D expenditures, demand-side policies, and the EPS index along with the share of environmental tax revenue, which are both utilized as alternative regulatory measures. In addition exchange rates and country-specific deflators are used from the OECD. While the International Energy Agency (2013) provides additional information on energy prices, the shadow prices of energy are taken from Althammer and Hille (2016). Data on supply-side policies is obtained from the World Bank (2017b).

4 Results and Discussion

4.1 Results for the Shadow and Energy Prices

While Table 2 reports the results of the FE and system GMM estimations when the shadow prices of energy are utilized as the measure of environmental regulation, Table 3 displays the respective results for the energy prices. The GMM results thereby address the potential endogeneity of environmental regulation, innovation, and trade openness by instrumenting their lagged values and first differences in the estimation. The validity of the instruments is confirmed with the help of the Hansen test of overidentifying restrictions, as well as the Arellano-Bond test for second-order serial correlation. For all GMM estimations, both null hypotheses of joint exogenous instruments and no serial correlation of the error term cannot be rejected. In addition, the validity of the individual instruments has been confirmed by separate difference-in-Hansen statistics, which are available upon request.

Four different specifications of Eq. (4) are estimated using the two cost-based policy stringency measures. The first specification represents a baseline specification, which extends the neo-Schumpeterian model of MFP growth to allow for environmental regulation effects. In addition, fixed effects including the $Crises$ covariate are controlled for. In the second specification, all control variables except for the innovation measures are added to the baseline specification. Hence, the environmental policy coefficient estimates of the first and second

[26] The dataset does not include the most recent years, because sector-specific data on the gross energy use of the seven energy carriers, which is needed to estimate the energy prices and update the shadow prices, are not yet available in the World Input-Output Database for those years.

Table 2 Estimation results environmental regulation-productivity nexus using shadow prices of energy

$MFP\ growth$	(1) FE	(2) GMM	(3) FE	(4) GMM	(5) FE	(6) GMM	(7) FE	(8) GMM
$ShadowP_{MovAv}$	0.021**	− 0.021***	0.019*	− 0.016***	0.027**	− 0.005	0.045***	0.006
	(0.011)	(0.006)	(0.010)	(0.005)	(0.011)	(0.005)	(0.010)	(0.006)
$MFPGap_{t-1}$	0.021***	0.012***	0.021***	0.014***	0.021***	0.021***	0.029***	0.028***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
$MFPLeader$	− 0.002	0.018***	− 0.003	0.021***	− 0.005	0.015***	− 0.003	0.009*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$(HSLabor/VA)_{t-1}$					0.167***	0.149***	0.139***	0.171***
					(0.035)	(0.027)	(0.038)	(0.040)
$(Patents/VA)_{t-1}$					0.251*	0.153	0.456***	0.551***
					(0.139)	(0.105)	(0.128)	(0.150)
$(R\&D/VA)_{t-1}$							0.072**	− 0.010
							(0.032)	(0.018)
$Crisis$	− 0.020***	− 0.020***	− 0.016***	− 0.014***	− 0.017***	− 0.017***	− 0.020***	− 0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Trade\ Openness_{t-1}$			0.005	0.004**	0.006*	0.003**	0.001	0.002
			(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$SSPolicy_{t-1}$			− 0.026***	0.003**	− 0.021***	0.005***	− 0.030***	0.006***
			(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.002)
$DSPolicy_{t-1}$			0.021***	0.019***	0.022***	0.009*	0.020***	0.014***
			(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$(ENUSE/VA)_{t-1}$			0.003	− 0.001**	0.000	− 0.002**	0.034***	0.001
			(0.002)	(0.001)	(0.002)	(0.001)	(0.009)	(0.002)

Table 2 continued

MFP growth	(1) FE	(2) GMM	(3) FE	(4) GMM	(5) FE	(6) GMM	(7) FE	(8) GMM
Constant	− 0.026***	0.013***	0.006	0.003	− 0.032**	− 0.036***	− 0.045***	− 0.053***
	(0.009)	(0.003)	(0.009)	(0.004)	(0.013)	(0.009)	(0.014)	(0.013)
Observations	4958	4958	4958	4958	4958	4958	3955	3955
F	15.3***		14.1***		15.7***		13.8***	
R^2_{adj}	0.072		0.090		0.103		0.166	
R^2_{within}	0.075		0.093		0.107		0.171	
Wald		234.5***		229.1***		253.4***		248.3***
AR(1)		− 9.504***		− 9.488***		− 9.400***		− 8.032***
AR(2)		− 0.959		− 0.953		− 0.972		0.543
Hansen		274.8		360.3		372.7		303.8
$Hansen_{df}$		262		328		339		286

Heteroskedasticity-corrected standard errors in parentheses
MovAv = lagged two-period moving average; FE = Fixed effect estimator; GMM = system generalized method of moments estimator
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 3 Estimation results environmental regulation-productivity nexus using energy prices

MFP growth	(9) FE	(10) GMM	(11) FE	(12) GMM	(13) FE	(14) GMM	(15) FE	(16) GMM
$EnergyP_{MovAv}$	0.024*	− 0.026***	0.021	− 0.022***	0.028**	− 0.004	0.049***	0.011
	(0.014)	(0.008)	(0.013)	(0.007)	(0.014)	(0.006)	(0.012)	(0.007)
$MFPGap_{t-1}$	0.024***	0.017***	0.024***	0.019***	0.024***	0.024***	0.031***	0.030***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)
$MFPLeader$	− 0.001	0.020***	− 0.002	0.025***	− 0.004	0.017***	− 0.003	0.009*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$(HSLabor/VA)_{t-1}$					0.157***	0.115***	0.126***	0.145***
					(0.035)	(0.027)	(0.038)	(0.044)
$(Patents/VA)_{t-1}$					0.257*	0.144	0.305*	0.079
					(0.138)	(0.102)	(0.156)	(0.305)
$(R\&D/VA)_{t-1}$							0.124***	0.074
							(0.044)	(0.053)
$Crisis$	− 0.020***	− 0.017***	− 0.016***	− 0.014***	− 0.017***	− 0.017***	− 0.020***	− 0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
$Trade\ Openness_{t-1}$			0.006*	0.006***	0.006*	0.004*	0.001	0.001
			(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$SSPolicy_{t-1}$			− 0.025***	0.003**	− 0.020***	0.005***	− 0.029***	0.007***
			(0.007)	(0.002)	(0.007)	(0.001)	(0.007)	(0.002)
$DSPolicy_{t-1}$			0.020***	0.018***	0.022***	0.012**	0.019***	0.016***
			(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$(ENUSE/VA)_{t-1}$			0.003	− 0.001**	0.001	− 0.001*	0.036***	− 0.001
			(0.002)	(0.001)	(0.002)	(0.001)	(0.010)	(0.003)

Table 3 continued

MFP growth	(9) FE	(10) GMM	(11) FE	(12) GMM	(13) FE	(14) GMM	(15) FE	(16) GMM
Constant	− 0.031**	0.013**	0.001	0.002	− 0.035**	− 0.034***	− 0.050***	− 0.055***
	(0.012)	(0.005)	(0.011)	(0.006)	(0.015)	(0.009)	(0.014)	(0.014)
Observations	4972	4972	4972	4972	4972	4972	3958	3958
F	15.3***		14.2***		15.7***		13.2***	
R^2_{adj}	0.079		0.097		0.109		0.198	
R^2_{within}	0.076		0.093		0.106		0.193	
Wald		202.1***		230.4***		240.8***		242.0***
AR(1)		− 9.491***		− 9.494***		− 9.419***		− 8.008***
AR(2)		− 1.083		− 1.085		− 1.101		0.194
Hansen		256.3		352.3		357.2		302.3
$Hansen_{df}$		262		328		339		286

Heteroskedasticity-corrected standard errors in parentheses

MovAv = lagged two-period moving average; FE = Fixed effect estimator; GMM = system generalized method of moments estimator

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

specification primarily reflect the direct regulatory effect on MFP growth, given that the potential indirect effect through innovation cannot be captured.[27] In the third and fourth specification, the innovation measures are included. Accordingly, the firm RD expenditures are only added in the fourth model, given the limited data availability for the Benelux countries and Ireland. The environmental regulation coefficient estimates in the third and fourth specification can account for the regulation-innovation relationship and, consequently, reflect the net effect of the direct and the indirect regulatory effect on MFP growth.[28]

Starting with the results of the baseline specification in Table 2, a positive and significant coefficient is estimated for the shadow prices of energy $ShadowP$ in the FE estimation in column (1). By contrast, the GMM estimates in column (2) display a significantly negative coefficient. In other words, while the FE estimates support the strong PH, the evidence changes significantly once simultaneity is controlled for. Increases in compliance costs seem to have a negative direct effect on MFP growth. This is similar to the first observations in the descriptive Sect. 3.4, which detect no or partly negative relationships in the regulation-productivity growth scatter plots. As expected from the theory, the coefficient estimates of the technological gap $MFPGap$ and technological frontier $MFPLeader$ are mainly positive and significant, confirming the importance of technological catch-up and pass-through processes for sectoral productivity growth. Moreover, the significantly negative coefficients of the $Crises$ fixed effect reflect the anticipated deterioration of the world financial crisis.

When the control variables are added in the second specification in columns (3) and (4), the coefficient estimates of the shadow prices only change slightly, yielding the same evidence on the strong PH. Likewise, the signs and significance levels of the coefficients of the $MFPGap$, $MFPLeader$, and $Crises$ variables remain stable. With regard to the control variables, increases in $Trade\ Openness$, along with more favorable macroeconomic supply-side policies $SSPolicy$ and demand-side policies $DSPolicy$, are found to facilitate sectoral productivity growth once simultaneity concerns are addressed. By contrast, the corresponding coefficient of the energy intensity $ENUSE/VA$ is significantly negative, indicating that sectors with an increased energy intensity are not more successful in raising MFP growth.

Interestingly, after including the two innovation measures $HSLabor/VA$ and $Patents/VA$ in the third specification in columns (5) and (6), the shadow price coefficient estimate remains positive and significant in the FE estimation, whereas that in the GMM estimation is no longer significant. The same can be observed for the fourth specification in columns (7) and (8), which includes all explanatory variables. Hence, contrary to the increasing evidence for the strong PH in the more recent literature, this paper finds that overall environmental policy stringency has no effect on MFP growth. One reason for the different results may stem from the fact that several of these studies do not or only partly account for potentially endogenous regressors. The estimates of the shadow price coefficients

[27] In this context, it should be mentioned that the environmental regulation coefficient estimates may also capture indirect effects on MFP growth, but only to the extent that they are linked to environmental policy stringency and not to innovation. These indirect effects are expected to slightly reduce the magnitude of the direct effect estimates and, hence, the estimates may be interpreted as a lower boundary for the extent that increases in regulatory stringency result directly in reduced MFP growth.

[28] When interpreting the regulation-induced innovation effects, it should be noted that not only innovations, which are primarily triggered through stricter environmental regulations, are included in the estimation, but also innovations that are driven by other motives, e.g. by market pressures to maintain a competitive edge. Moreover, the findings of the earlier specifications remain the same if they are re-estimated using the smaller sample of the fourth specification. For examples of the third specification using the Törnqvist (1936) and Ackerberg et al. (2015) MFP growth measures, see columns (45) and (46) in Table 10 in “Appendix C” as well as columns (33) and (34) in Table 5 in “Appendix A” respectively.

provide a good example that disregarding endogeneity may lead to biased support for the strong PH.

Moreover, the change in the sign of the shadow price coefficients in the GMM estimations from significantly negative values in columns (2) and (4) to insignificant values in columns (6) and (8) is an indication that parts of the impact of environmental policy on productivity can be attributed to innovations induced by stricter regulation. To better capture this channel, the indirect effect is also estimated using interaction terms of the innovation and environmental regulation variables. For example, in columns (43) and (44) in Table 9 in "Appendix C" the results are shown for a specification that includes one interaction term of regulation with an upstream measure of innovation, i.e. $R\&D/VA$, and one with an intermediate-step measure of the innovative process, i.e. $Patents/VA$. Interestingly, the GMM results in column (48) reveal a significantly negative coefficient of the shadow prices and a significantly positive coefficient of the interaction term with $R\&D/VA$. The positive relationship between regulatory stringency and innovation, which is frequently detected in the literature (Brunnermeier and Cohen 2003; Jaffe and Palmer 1997; Carrión-Flores and Innes 2010), can also be found when the environmental policy-innovation nexus is estimated directly. For instance, Table 11 in "Appendix D" reports significantly positive effects of increases in the shadow prices on the triadic patent counts. Therefore, apart from the negative direct effect of environmental regulation on MFP growth, a positive indirect effect through innovation seems to exist. Overall, both effects balance out, providing support for the weak PH.

Even though the positive indirect effect does not outweigh the direct negative effect, it is important to recognize that environmental regulations may induce green innovations, which lead to additional benefits that are not or only partly reflected in the traditional productivity measure. For instance, green innovations may clean up the environment (Lee and Min 2015), entail a more careful use of natural resource inputs, and improve safety and the quality of life (Hellström 2007). Stricter environmental regulations may foster the cooperation of firms with external partners to develop green innovations (de Marchi 2012) that are potentially in the public interest, but for which the individual firms would not have the necessary capabilities. The regulatory forces may also facilitate more transparent communication of firms with stakeholders and local decision-makers, so that they comply with regulations and build up trust (Hooghiemstra 2000).

In contrast to the net effect of regulation-induced innovation, innovation efforts in general are found to be an important driver of sectoral productivity growth. This corresponds to the first observations on the innovation-productivity growth relationship in the descriptive Sect. 3.4. Except for two insignificant values, only positive and significant coefficients are estimated in columns (5)–(8) for the high-skill labor compensation per value added $HSLabor/VA$, the triadic patent counts per value added $Patents/VA$, and the firm R&D expenditures per value added $R\&D/VA$.[29]

The estimation results in Table 3 using energy prices as the measure of regulatory stringency generally confirm the prior findings. While some evidence for the strong PH can be detected in the FE estimates in the odd columns, the positive impact of increases in industrial energy prices $EnergyP$ on MFP growth disappears once simultaneity is controlled for in the GMM estimates in the even columns. Accordingly, the negative energy price coefficients in columns (10) and (12) are an indication of the negative direct effect of higher compli-

[29] In order to determine how some zero observations in the $Patents/VA$ variable affect the results of the innovation channel, $Patents/VA$ are excluded from the estimation in columns (41) and (42) in Table 9 in "Appendix C". As can be seen, the results are fairly robust in comparison to the prior ones in columns (7) and (8) in Table 2. The only striking, but expected, difference is that the $R\&D/VA$ coefficients took up some of the explanatory power of the omitted innovation term.

ance costs. The corresponding insignificant coefficients in columns (14) and (16) show that the overall net effect on MFP growth is close to zero, once the indirect policy effect through regulation-induced innovations is taken into account. Hence, energy prices are also positively related with innovation efforts. The coefficients of the remaining covariates, as well as their level of significance, are fairly similar to the estimates in Table 2 utilizing the shadow prices as the measure of regulatory stringency.

4.2 Comparison to Alternative Environmental Policy Measures

The results for the final specification, using the alternative measures of environmental policy stringency, are shown in Table 4.[30] The coefficient estimates of the regulatory measures yield predominantly two findings that correspond to the estimation results of the two cost-based measures. First, the significantly positive coefficient estimates, which are found for all FE estimations in the odd columns, change to insignificant or significantly negative coefficients for four out of five regulatory measures, once simultaneity is controlled for in the even columns. Thus, also for the alternative environmental regulation measures, disregarding the potential endogeneity of the environmental regulation, innovation, and trade openness covariates may result in upward biased estimates of the regulatory effect on MFP growth. Second, no support for the strong PH can generally be detected in the GMM estimates. As for the shadow prices and energy prices, insignificant overall effects are found for three alternative measures, namely the emission-based measures $-\Delta SO_X/VA$ and $-\Delta NO_X/VA$ as well as the EPS index measure $EPS(ENUSE/VA)$. For the share of environmental tax revenue $EnvTax$, the direct effect in the form of the opportunity costs of higher taxes seems to outweigh the benefits on productivity growth of induced innovations. However, this measure only considers environmental taxes and excludes the effects of other instruments in the policy mix, such as subsidies, tradable permits, or pollution standards. By its very nature, national tax revenue also cannot account for heterogeneous effects on MFP growth across sectors within countries.

Interestingly, the CO_2 emissions measure $-\Delta CO_2/VA$ is the only regulatory measure for which a positive coefficient is still estimated after taking simultaneity into account.[31] This result may be explained by several interrelated points. First, while the local air pollutants have been regulated relatively early since the 1960s and 1970s, such as through command-and-control regulations in the form of the US and UK Clean Air Acts, global air pollutants have only been regulated more recently, predominantly through market-based instruments such as the EU Emission Trading System. Consequently, it is likely that during the last few years firms, had to react particularly to the new carbon regulations by increasing their innovation activities and reorganizing production processes. Second, the result may stem from concerns about carbon leakage. Being well aware that firms can relocate economic activity to countries with less stringent climate regulations, policy makers may tend to carefully balance global environmental benefits and the effects on the national industrial competitiveness before passing new regulations. If, as a result, firms reduce their carbon intensities, this may have

[30] The evidence on the strong PH and potential endogeneity bias does not change significantly when the third specification is estimated instead of the fourth.

[31] The sources of emissions, and policies to regulate them, are partly related to each other, especially those of emissions with local effects. Therefore, an omitted variable bias may occur when using only one emission-based measure at a time to proxy environmental policy stringency. In order to address this concern, all three emission-based measures are included as explanatory variables in columns (37) and (38) in Table 9 in “Appendix C”. As can be seen, the positive effect of the CO_2 emissions measure and the insignificant effects of the SO_X and NO_X emissions measures remain the same in the GMM estimations.

Table 4 Estimation results using alternative regulatory measures

MFP growth	(17) FE	(18) GMM	(19) FE	(20) GMM	(21) FE	(22) GMM	(23) FE	(24) GMM	(25) FE	(26) GMM
$-(\Delta SO_X/VA)_{MovAv}$	1.540**	0.783								
	(0.619)	(0.491)								
$-(\Delta NO_X/VA)_{MovAv}$			4.178**	1.454						
			(1.893)	(2.196)						
$-(\Delta CO_2/VA)_{MovAv}$					6.839***	7.182***				
					(0.545)	(1.116)				
$(EPS(ENUSE/VA))_{MovAv}$							0.063*	0.001		
							(0.037)	(0.026)		
$EnvTax_{MovAv}$									0.003***	− 0.001***
									(0.001)	(0.000)
$MFPGap_{t-1}$	0.029***	0.026***	0.029***	0.027***	0.028***	0.026***	0.034***	0.030***	0.027***	0.032***
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.006)	(0.008)	(0.005)	(0.008)
$MFPLeader$	0.006	0.017***	0.006	0.017***	0.006	0.017***	− 0.003	0.009**	− 0.001	0.004
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
$(HSLabor/VA)_{t-1}$	0.110***	0.104***	0.106***	0.122***	0.102***	0.108***	0.113***	0.140***	0.119***	0.164***
	(0.036)	(0.026)	(0.036)	(0.028)	(0.037)	(0.026)	(0.039)	(0.043)	(0.035)	(0.031)
$(Patents/VA)_{t-1}$	0.570***	0.313	0.569***	0.612**	0.604***	0.347*	0.456***	0.268**	0.543***	0.580**
	(0.145)	(0.266)	(0.145)	(0.282)	(0.148)	(0.181)	(0.133)	(0.123)	(0.121)	(0.291)
$(R\&D/VA)_{t-1}$	0.063***	0.051	0.061***	− 0.002	0.048**	0.045**	0.075**	0.007	0.048**	− 0.021
	(0.022)	(0.041)	(0.022)	(0.042)	(0.024)	(0.022)	(0.032)	(0.016)	(0.023)	(0.044)
$Crisis$	− 0.013***	− 0.018***	− 0.013***	− 0.018***	− 0.013***	− 0.018***	− 0.015***	− 0.017***	− 0.014***	− 0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Trade\ Openness_{t-1}$	0.003	0.002	0.003	0.003*	0.002	0.002	0.001	0.002	0.004	0.002

Table 4 continued

MFP growth	(17) FE	(18) GMM	(19) FE	(20) GMM	(21) FE	(22) GMM	(23) FE	(24) GMM	(25) FE	(26) GMM
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$SSPolicy_{t-1}$	− 0.028***	0.005***	− 0.027***	0.005***	− 0.029***	0.004***	− 0.028***	0.006***	− 0.020***	0.005***
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.008)	(0.002)	(0.007)	(0.002)
$DSPolicy_{t-1}$	0.045***	0.013**	0.044***	0.013*	0.044***	0.014**	0.026***	0.022***	0.019***	0.017***
	(0.008)	(0.006)	(0.008)	(0.007)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
$(ENUSE/VA)_{t-1}$	0.034***	− 0.001	0.033***	0.001	0.034***	0.000	0.031***	− 0.002	0.024***	− 0.003
	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.005)	(0.009)	(0.003)
Constant	− 0.005	− 0.038***	− 0.005	− 0.041***	− 0.001	− 0.037***	− 0.011	− 0.040***	− 0.040***	− 0.039***
	(0.011)	(0.009)	(0.011)	(0.009)	(0.012)	(0.009)	(0.012)	(0.013)	(0.012)	(0.009)
Observations	3708	3708	3718	3718	3718	3718	3636	3636	3922	3922
F	22.9***		25.3***		92.4***		12.8***		21.1***	
R^2_{adj}	0.186		0.185		0.189		0.154		0.162	
R^2_{within}	0.191		0.189		0.193		0.159		0.167	
Wald		220.2***		210.0***		1783.4***		225.5***		257.0***
AR(1)		− 7.608***		− 7.560***		− 7.708***		− 7.680***		− 8.005***
AR(2)		0.034		− 0.030		0.108		1.281		− 1.157
Hansen		280.9		279.8		279.8		270.1		294.5
$Hansen_{df}$		258		258		258		249		278

Heteroskedasticity-corrected standard errors in parentheses

MovAv = lagged two-period moving average; FE = Fixed effect estimator; GMM = system generalized method of moments estimator. In order to make the coefficient estimates of the environmental regulation measures comparable the emission-based measures are multiplied by − 1

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

a sustainable impact on productivity growth. Third, as the CO_2 emissions are regulated predominantly through market-based instruments, the positive coefficient is in line with several studies on the narrow version of the PH (Ambec et al. 2013; Cohen and Tubb 2018). These studies revealed that market-based instruments give firms more incentives to innovate, and thus lead to higher productivity. Last, reductions in CO_2 emissions can be the result of other things than climate policy, that are also reflected in the emission-based measure. The reductions can be a by-product of increases in energy efficiency or other related energy advances, such as advances in hydraulic fracturing that made natural gas cheaper than coal in the US in the late 2000s.

The coefficients of the remaining explanatory variables are fairly robust to changes in the regulatory measure and similar to those in Sect. 4.1. All things considered, the estimations of the alternative measures produce, despite the inherent measurement problems, mostly comparable evidence on the strong PH and on endogeneity bias.

5 Conclusion

Despite the vast research efforts during the last decades, evidence on the strong PH is far from conclusive. Possible explanations for the mixed results range from the insufficient control of endogenous regressors, to measurement problems associated with the environmental policy variable, to the use of restricted sectoral datasets mostly covering a limited number of highly developed countries.

This paper addresses each of the above points.[32] The paper clearly shows that disregarding endogeneity concerns significantly alters the regulatory effects on productivity growth and, hence, leads to biased estimates. Specifically, the FE estimates reveal significantly positive overall effects of environmental policy stringency on productivity growth. After taking simultaneity into account, the corresponding coefficient estimates become mostly insignificant and partly negative. Thus, contrary to the results of the more recent studies, which often do not or only partly control for potentially endogenous explanatory variables, the paper finds no evidence for the strong PH. While accounting for simultaneity significantly changes the evidence on the strong PH, the findings mostly remain unchanged when alternative environmental regulation measures are used. In that regard, the paper helps in reconciling some of the conflicting evidence of previous analyses. In contrast to the overall environmental regulation effect, innovation, technology transfers, and sound supply- and demand-side policies are identified as significant drivers of sectoral productivity growth. Given that environmental regulation is positively related to innovation, the results indicate that the weak PH is valid. Hence, by inducing innovation efforts, such as in the form of new triadic patent applications, stricter environmental regulation has an indirect positive effect on productivity growth. Yet, the productivity gains are fully counterbalanced by the costs of complying with the more stringent environmental policy.

The findings have important policy implications. Even though no evidence for the strong PH is revealed, for most of the regulatory measures, increases in policy stringency have

[32] While the dataset certainly represents an improvement over prior cross-country sectoral studies, the authors acknowledge that some limitations remain. On the one hand, subject to data availability, the inclusion of further emerging economies may help in analyzing how the importance of the drivers of sectoral productivity growth changes with the level of development of the respective countries' industries. On the other hand, a finer level of disaggregation in the form of international firm-level data would provide more precise estimates of individual responses to stricter environmental regulation. Hence, such an analysis may help reveal the firm characteristics that are essential for transforming higher compliance costs into productivity gains.

no negative impact on productivity growth. As long as firms are able to benefit from their environmental initiatives in the form of process and product innovations, (well-crafted) environmental regulations do not erode sectoral competitiveness. Even better, besides offsetting the additional costs of pollution abatement, the induced (green) innovations may lead to additional benefits, such as protecting the environment and improving safety and the quality of life, which are not or only partly reflected in the traditional productivity measure. For politicians concerned about the competitiveness of national industries, these findings are good, but not perfect news. It is equally important to recognize that the insignificant productivity effects across countries are average terms. A subset of industries and firms may lose competitiveness and, consequently, legitimately raise concerns about stricter regulations. Sectors that bear significant compliance costs from environmental and energy regulation have been detected in the literature (Sato et al. 2015a; Wang et al. 2017). A well-designed policy mix needs to explicitly account for these sectoral differences. Hence, further research is required on the question of which specific policies jointly ensure environmental protection and induce innovations that are successful in fostering productivity growth. In addition, it is necessary to know how these policies interact with each other.

Appendix A: Regression Results of the Ackerberg et al. (2015) MFP Measure

See Table 5.

Table 5 Estimation results of the Ackerberg et al. (2015) MFP measure using shadow prices of energy

MFP growth	1st specification		2nd specification		3rd specification		3rd specification (small)		4th specification	
Ackerberg et al. (2015)	(27) FE	(28) GMM	(29) FE	(30) GMM	(31) FE	(32) GMM	(33) FE	(34) GMM	(35) FE	(36) GMM
$ShadowP_{MovAv}$	0.146***	− 0.004*	0.017***	− 0.003	0.021***	0.004	0.033***	0.004	0.031***	0.004
	(0.029)	(0.002)	(0.006)	(0.003)	− 0.006	(0.003)	(0.006)	(0.004)	(0.006)	(0.003)
$MFPGap_{t-1}$	0.023	0.021***	0.079***	0.031***	0.074***	0.024***	0.075***	0.034***	0.074***	0.039***
	− 0.04	(0.006)	(0.009)	(0.007)	(0.010)	(0.007)	(0.011)	(0.012)	(0.011)	(0.011)
$MFPLeader$	− 0.017	0.046***	0.035***	0.036***	0.033***	0.044***	0.034***	0.052**	0.034***	0.051**
	(0.017)	(0.012)	(0.009)	(0.010)	(0.009)	(0.014)	(0.012)	(0.021)	(0.012)	(0.020)
$(HSLabor/VA)_{t-1}$					0.081***	0.031**	0.086**	0.010	0.076**	0.010
					(0.030)	(0.014)	(0.036)	(0.015)	(0.034)	(0.014)
$(Patents/VA)_{t-1}$					0.074	0.032	0.303**	0.239**	0.102	0.035
					(0.058)	(0.053)	(0.118)	(0.100)	(0.144)	(0.113)
$(R\&D/VA)_{t-1}$									0.073***	0.033**
									(0.018)	(0.015)
$Crisis$	− 0.228***	0.005***	0.004**	0.006***	0.003*	0.005***	0.003*	0.006***	0.004*	0.006***
	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$Trade\ Openness_{t-1}$			− 0.001	0.001	− 0.001	0.001	− 0.001	0.001	− 0.001	0.001
			(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
$SSPolicy_{t-1}$			− 0.008*	0.001***	− 0.006	0.001***	− 0.013**	0.002***	− 0.012**	0.002***
			(0.004)	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
$DSPolicy_{t-1}$			0.007*	0.007**	0.008*	0.006*	0.008*	0.009**	0.008*	0.009**
			(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)

Table 5 continued

MFP growth	1st specification		2nd specification		3rd specification		3rd specification (small)		4th specification	
Ackerberg et al. (2015)	(27) FE	(28) GMM	(29) FE	(30) GMM	(31) FE	(32) GMM	(33) FE	(34) GMM	(35) FE	(36) GMM
$(ENUSE/VA)_{t-1}$			0.002*	− 0.002*	0.001	− 0.001	0.029***	− 0.001	0.027***	− 0.002
			(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.002)	(0.006)	(0.002)
Constant	− 0.045*	− 0.001	− 0.016**	− 0.004	− 0.034***	− 0.014***	− 0.041***	− 0.014***	− 0.041***	− 0.015***
	(0.025)	(0.002)	(0.007)	(0.002)	(0.010)	(0.004)	(0.011)	(0.005)	(0.011)	(0.004)
Observations	4957	4957	4957	4957	4957	4957	3955	3955	3955	3955
F	90.59***		13.38***		12.14***		11.60***		11.97***	
R^2_{adj}	0.271		0.079		0.082		0.119		0.122	
R^2_{within}	0.273		0.082		0.086		0.123		0.127	
Wald		138.6***		162.1***		172.3***		137.0***		154.3***
AR(1)		− 7.917***		− 7.869***		− 7.866***		− 6.686***		− 6.633***
AR(2)		− 0.029		− 0.065		− 0.048		− 0.027		− 0.043
Hansen		281.6		302.2		335.9		265.4		288.6
$Hansen_{df}$		274		294		316		239		279

Heteroskedasticity-corrected standard errors in parentheses

MovAv = lagged two-period moving average; FE = Fixed effect estimator; GMM = system generalized method of moments estimator

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix B: Descriptive Statistics and Variables Overview

See Tables 6, 7 and 8.

Table 6 Descriptive statistics by country and manufacturing sector

Medians by country	$MFP\ growth$	$Shadow P_{MovAv}$	$Patents/VA$[a]	$R\&D/VA$
Australia	−0.010	0.449	1.186	0.016
Austria	0.009	0.550	1.803	0.025
Belgium	0.004	0.617	1.484	–
Canada	0.010	0.515	0.615	0.017
Czech Republic	0.004	0.756	0.019	0.008
Denmark	−0.001	0.526	3.487	0.052
Estonia	−0.003	0.858	0.000	0.007
Finland	0.001	0.492	2.359	0.023
France	0.008	0.461	3.435	0.025
Germany	0.011	0.621	3.706	0.019
Greece	−0.005	0.712	0.000	0.003
Hungary	−0.008	1.181	0.065	0.002
Ireland	0.004	0.698	0.273	–
Italy	−0.001	0.956	0.722	0.004
Japan	0.005	0.654	3.905	0.062
Korea	0.003	0.773	0.617	0.013
Luxembourg	0.000	4.571	0.005	–
Mexico	−0.034	0.897	0.009	0.001
Netherlands	0.005	2.762	0.003	–
Poland	0.001	0.770	0.000	0.003
Portugal	0.003	0.958	0.000	0.005
Slovak Republic	0.008	1.062	0.000	0.006
Slovenia	−0.004	1.217	0.000	0.009
Spain	−0.001	0.666	0.174	0.009
Sweden	0.001	0.514	4.168	0.019
Turkey	−0.059	1.014	0.000	0.001
United Kingdom	0.004	0.532	1.840	0.009
United States	0.001	0.465	1.861	0.024
Medians by manufacturing sector, ISIC Rev. 3.1				
15–16	−0.001	0.583	0.270	0.007
17–18	0.001	0.667	0.265	0.007
19	0.000	0.726	0.000	0.006
20	0.001	0.641	0.000	0.002
21–22	−0.001	0.653	0.086	0.004
23	−0.004	0.529	0.155	0.012

Table 6 continued

Medians by country	*MFP growth*	$Shadow P_{MovAv}$	$Patents/VA^{a}$	$R\&D/VA$
24	−0.003	0.577	14.705	0.058
25	0.001	0.790	0.226	0.016
26	−0.001	0.515	1.041	0.008
27–28	0.000	0.551	0.511	0.008
29	0.002	0.745	9.128	0.029
30–33	0.008	0.792	16.496	0.083
34–35	0.001	0.756	1.311	0.051
36–37	0.002	0.723	4.599	0.008

[a]Multiplied with 10^3; Units of measurement: MFP (Unit), $Shadow P_{MovAv}$ (2005 PPP \$K per toe), $PATENTS/VA$ (Number per 2005 PPP \$K) $R\&D/VA$ (2005 PPP \$ per 2005 PPP). ISIC Rev. 3.1 classification: 15–16 Food, beverages, and tobacco, 17–18 Textiles and textile products, 19 Leather, leather and footwear, 20 Wood and products of wood and cork, 21–22 Pulp, paper, printing, and publishing, 23 Coke, refined petroleum, and nuclear fuel, 24 Chemicals and chemical products, 25 Rubber and plastics, 26 Other non-metallic mineral, 27–28 Basic metals and fabricated metal, 29 Machinery, nec, 30–33 Electrical and optical equipment, 34–35 Transport equipment, 36–37 Manufacturing, nec; recycling

Table 7 Variables definition and units of measurement

Variable	Description	Unit
Empirical model		
MFPGrowth	Multifactor productivity growth	Unit
$Shadow P_{MovAv}$	Shadow prices of emission relevant energy	2005 PPP $K per toe
$Energy P_{MovAv}$	Energy prices	2005 PPP $K per toe
$(\Delta SO_X/VA)_{MovAv}$	Change in sulfur oxide emissions per value added	g per 2005 PPP $bn
$(\Delta NO_X/VA)_{MovAv}$	Change in nitrogen oxide emissions per value added	g per 2005 PPP $bn
$(\Delta CO_2/VA)_{MovAv}$	Change in carbon monoxide emissions per value added	kg per 2005 PPP $bn
$(EPS(ENUSE/VA))_{MovAv}$	Environmental Policy Stringency index multiplied with the sectoral pollution intensity	Index x toe per 2005 PPP $K
$EnvTax_{MovAv}$	Environmentally related tax revenues	% of total tax revenues
$MFPGap$	Difference to highest sectoral MFP level in year *t*	Level
$MFPLeader$	Highest sectoral MFP level in year *t*	Level
$Trade\ Openness$	Trade openness	2005 PPP $ per 2005 PPP $m
$HSLabor/VA$	High-skill labor compensation per value added	2005 PPP $ per 2005 PPP $
$Patents/VA$	Triadic patents per value added	Number per 2005 PPP $K
$Patents$	Triadic patents	Number

Table 7 continued

Variable	Description	Unit
$R\&D/VA$	R&D expenditures of business enterprises per value added	2005 PPP \$ per 2005 PPP \$m
$SSPolicy$	Regulatory Quality Index	Index [– 2.5; 2.5]
$DSPolicy$	Monetary and fiscal policy index	Index [-1.07; 0]
$ENUSE/VA$	Gross energy use per value added	toe per 2005 PPP \$K
Determination of MFP growth		
Y_{cit}	Gross output	2005 PPP \$bn
X_{cit}	Intermediate inputs	2005 PPP \$bn
K_{cit}	Capital stock	2005 PPP \$bn
L_{cit}	Labor input	Hours per persons engaged
$P_{X,cit}$	Costs for intermediate inputs	2005 PPP \$bn
$P_{L,cit}$	Labor compensation	2005 PPP \$bn
$P_{K,cit}$	Capital compensation	2005 PPP \$bn

MovAv = lagged two-period moving average

Table 8 Summary statistics

Variable	Median	Mean	SD
MFP	0.000	−0.003	0.039
$ShadowP_{MovAv}$	0.650	0.720	0.287
$EnergyP_{MovAv}$	0.645	0.719	0.284
$(\Delta SO_X/VA)^{a}_{MovAv}$	0.013	0.140	1.277
$(\Delta NO_X/VA)^{a}_{MovAv}$	0.009	0.043	0.924
$(\Delta CO_2/VA)^{a}_{MovAv}$	0.000	0.005	0.334
$(EPS(ENUSE/VA))_{MovAv}$	0.016	0.054	0.103
$EnvTax_{MovAv}$	7.124	7.302	2.513
$MFPGap$	0.640	0.685	0.425
$MFPLeader$	0.000	0.068	0.360
$Trade\ Openness$	0.725	0.903	0.753
$HSLabor/VA$	0.118	0.132	0.073
$Patents/VA^{a}$	0.587	5.866	15.709
$Patents$	2.000	122.674	616.937
$R\&D/VA$	0.011	0.039	0.084
$SSPolicy$	1.270	1.119	0.783
$DSPolicy$	−0.273	−0.279	0.250
$ENUSE/VA$	0.014	0.177	1.154

[a]Multiplied with 10^3

Appendix C: Additional Robustness Checks

See Tables 9 and 10.

Table 9 Estimation results of different robustness checks using shadow prices of energy

MFP growth	All emission measures		With sector fixed effects		No $Patents/VA$		Policy-innovation interactions	
	(37) FE	(38) GMM	(39) FE	(40) GMM	(41) FE	(42) GMM	(43) FE	(44) GMM
$ShadowP_{MovAv}$			0.045***	0.012	0.044***	0.001	0.034***	− 0.017**
			(0.010)	(0.007)	(0.010)	(0.005)	(0.010)	(0.007)
$ShadowP_{MovAv} \times (R\&D/VA)_{t-1}$							0.210	0.368*
							(0.146)	(0.213)
$ShadowP_{MovAv} \times (Patents/VA)_{t-1}$							− 1.251	− 0.833
							(0.876)	(1.096)
$-(\Delta CO_2/VA)_{MovAv}$	6.114***	5.746**						
	(0.807)	(2.541)						
$-(\Delta SO_X/VA)_{MovAv}$	0.951	− 1.233						
	(0.881)	(1.137)						
$-(\Delta NO_X/VA)_{MovAv}$	0.972	8.617						
	(1.887)	(7.334)						
$MFPGap_{t-1}$	0.028***	0.030***	0.029***	0.031***	0.029***	0.031***	0.029***	0.025***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
$MFPLeader$	0.005	0.020***	− 0.003	0.009**	− 0.003	0.007	− 0.001	0.018***
	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$(HSLabor/VA)_{t-1}$	0.105***	0.097***	0.139***	0.169***	0.140***	0.196***		
	(0.037)	(0.028)	(0.037)	(0.043)	(0.036)	(0.039)		
$(Patents/VA)_{t-1}$	0.602***	0.208	0.456***	0.808***			1.301**	1.141*
	(0.147)	(0.326)	(0.128)	(0.251)			(0.525)	(0.663)
$(R\&D/VA)_{t-1}$	0.051**	0.053	0.071**	− 0.002	0.098***	0.060***	− 0.064	− 0.220
	(0.023)	(0.054)	(0.031)	(0.026)	(0.031)	(0.016)	(0.095)	(0.135)

Table 9 continued

$MFP\ growth$	All emission measures		With sector fixed effects		No $Patents/VA$		Policy-innovation interactions	
	(37) FE	(38) GMM	(39) FE	(40) GMM	(41) FE	(42) GMM	(43) FE	(44) GMM
$Crisis$	− 0.012***	− 0.017***	− 0.019***	− 0.018***	− 0.020***	− 0.018***	− 0.018***	− 0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Trade\ Openness_{t-1}$	0.002	0.002	0.001	0.002	0.001	0.001	− 0.001	0.002
	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
$SSPolicy_{t-1}$	− 0.028***	0.004***	− 0.030***	0.006***	− 0.030***	0.006***	− 0.033***	0.004***
	(0.006)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.006)	(0.001)
$DSPolicy_{t-1}$	0.044***	0.014**	0.019***	0.015***	0.019***	0.009*	0.018***	0.021***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
$(ENUSE/VA)_{t-1}$	0.034***	− 0.001	0.033***	0.012**	0.033***	− 0.004	0.037***	− 0.004
	(0.008)	(0.002)	(0.009)	(0.005)	(0.009)	(0.002)	(0.009)	(0.003)
Constant	− 0.002	− 0.039***	− 0.045***	− 0.053***	− 0.043***	− 0.055***	− 0.012	− 0.006
	(0.011)	(0.009)	(0.014)	(0.014)	(0.013)	(0.012)	(0.010)	(0.005)
Observations	3708	3708	3955	3955	3955	3955	3955	3955
F	83.89***		13.82***		12.16***		12.73***	
R^2_{adj}	0.190		0.166		0.165		0.162	
R^2_{within}	0.195		0.171		0.169		0.167	
Wald		679.1***		288.3***		209.8***		244.2***
AR(1)		− 7.664***		− 7.986***		− 8.008***		− 8.178***
AR(2)		− 0.045		0.500		0.566		0.703
Hansen		296.7		300.8		300.3		286.9
$Hansen_{df}$		285		274		279		277

Heteroskedasticity-corrected standard errors in parentheses
MovAv = lagged two-period moving average; FE = Fixed effect estimator; GMM = system generalized method of moments estimator
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 10 Estimation results for different modifications of the third specification using shadow prices of energy

MFP growth	Small sample		Alterations of $MFPGap$ and $MFPLeader$					
	(45) FE	(46) GMM	(47) FE	(48) GMM	(49) FE	(50) GMM	(51) FE	(52) GMM
$ShadowP_{MovAv}$	0.046***	0.005	0.030**	− 0.003	0.030**	− 0.002	0.026**	− 0.004
	(0.010)	(0.005)	(0.012)	(0.004)	(0.012)	(0.004)	(0.011)	(0.004)
$MFPGap_{t-1}$	0.029***	0.030***					0.021***	0.015***
	(0.005)	(0.006)					(0.004)	(0.004)
$MFPLeader$	− 0.003	0.009**			− 0.008	0.010**		
	(0.004)	(0.004)			(0.005)	(0.004)		
$(HSLabor/VA)_{t-1}$	0.149***	0.191***	0.165***	0.095***	0.174***	0.124***	0.162***	0.092***
	(0.038)	(0.035)	(0.012)	(0.016)	(0.034)	(0.022)	(0.035)	(0.016)
$(Patents/VA)_{t-1}$	0.652***	0.592***	0.238*	0.164	0.235*	0.125	0.253*	0.183*
	(0.097)	(0.140)	(0.137)	(0.105)	(0.137)	(0.090)	(0.139)	(0.105)
$Crisis$	− 0.020***	− 0.018***	− 0.017***	− 0.015***	− 0.017***	− 0.017***	− 0.017***	− 0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Trade\ Openness_{t-1}$	0.001	0.001	0.004	0.004***	0.004	0.005***	0.005*	0.001
	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
$SSPolicy_{t-1}$	− 0.031***	0.006***	− 0.023***	0.002***	− 0.023***	0.002**	− 0.020***	0.004***
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	(0.006)	(0.001)
$DSPolicy_{t-1}$	0.019***	0.009*	0.021***	0.017**	0.022***	0.010*	0.021***	0.017***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)
$(ENUSE/VA)_{t-1}$	0.035***	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.009)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table 10 continued

MFP growth	Small sample		Alterations of $MFPGap$ and $MFPLeader$					
	(45) FE	(46) GMM	(47) FE	(48) GMM	(49) FE	(50) GMM	(51) FE	(52) GMM
Constant	− 0.045***	− 0.058***	− 0.016	− 0.010**	− 0.016	− 0.017***	− 0.032**	− 0.019***
	(0.014)	(0.011)	(0.014)	(0.005)	(0.014)	(0.006)	(0.012)	(0.006)
Observations	3955	3955	4958	4958	4958	4958	4958	4958
F	15.36***		16.83***		15.92***		16.38***	
R^2_{adj}	0.164		0.080		0.083		0.103	
R^2_{within}	0.169		0.084		0.087		0.106	
Wald		233.5***		275.5***		238.3***		258.1***
AR(1)		− 8.083***		− 9.389***		− 9.407***		− 9.393***
AR(2)		0.523		− 0.994		− 0.952		− 1.026
Hansen		294.4		382.8		373.4		383.9
$Hansen_{df}$		279		358		367		361

Heteroskedasticity-corrected standard errors in parentheses
MovAv = lagged two-period moving average; FE = Fixed effect estimator; GMM = system generalized method of moments estimator
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix D: Regression Results of the Environmental Regulation-Innovation Nexus

See Table 11.

Table 11 Estimation results environmental regulation-innovation nexus using the shadow prices of energy

$Patents$	(53) GMM	(54) GMM	(55) GMM	(56) GMM
$ShadowP_{MovAv}$	703.325**	645.388*		
	(354.233)	(343.592)		
$ShadowP_{t-1}$			486.716**	361.641*
			(241.717)	(217.105)
$ShadowP_{t-2}$			97.454	93.059
			(225.415)	(192.573)
$(HSLabor/VA)_{t-1}$	3397**	3899**	3208*	3567**
	(1697)	(1693)	(1700)	(1617)
$(R\&D/VA)_{t-1}$	8.209***	7.991***	8.239***	7.937***
	(2.489)	(2.372)	(2.545)	(2.378)
$Trade\ Openness_{t-1}$	− 124.400	− 118.840	− 105.636	− 93.367
	(78.185)	(72.248)	(73.860)	(62.760)
$Crisis$	− 67.798*	− 125.926***	− 55.070*	− 108.038**
	(36.785)	(48.816)	(33.126)	(42.125)
$SSPolicy_{t-1}$		− 5.413		− 22.077
		(40.749)		(36.021)
$DSPolicy_{t-1}$		− 532.265***		− 549.383***
		(163.481)		(165.933)
Constant	− 1.128**	− 1.265**	− 1.029**	− 1.073**
	(478.175)	(− 517.960)	(457.514)	(452.646)
Observations	3955	3955	3955	3955
Wald	24.05*	28.73*	28.26**	29.79*
AR(1)	− 0.586	− 0.826	− 0.651	− 0.843
AR(2)	− 1.362	− 1.579	− 1.418	− 1.551
Hansen	310.6	310.7	303.7	311.6
$Hansen_{df}$	291	291	277	281

Heteroskedasticity-corrected standard errors in parentheses
GMM = system generalized method of moments estimator
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

References

Acemoglu D, Aghion P, Zilibotti F (2006) Distance to frontier, selection, and economic growth. J Eur Econ Assoc 4(1):37–74

Ackerberg DA, Caves K, Frazer G (2015) Identification properties of recent production function estimators. Econometrica 83(6):2411–2451

Aghion P, Howitt P (2006) Joseph Schumpeter lecture: appropriate growth policy—a unifying framework. J Eur Econ Assoc 4(2–3):269–314
Aghion P, Dewatripont M, Rey P (1997) Corporate governance, competition policy and industrial policy. Eur Econ Rev 41(3–5):797–805
Albrizio S, Kozluk T, Zipperer V (2017) Environmental policies and productivity growth: evidence across industries and firms. J Environ Econ Manag 81:209–226
Aldy JE, Pizer WA (2015) The competitiveness impacts of climate change mitigation policies. J Assoc Environ Resour Econ 2(4):565–595
Alpay E, Buccola S, Kerkvliet J (2002) Productivity growth and environmental regulation in Mexican and U.S. food manufacturing. Am J Agric Econ 84(4):887–901
Althammer W, Hille E (2016) Measuring climate policy stringency: a shadow price approach. Int Tax Public Financ 23(4):607–639
Ambec S, Barla P (2002) A theoretical foundation of the Porter hypothesis. Econ Lett 75(3):355–360
Ambec S, Cohen MA, Elgie S, Lanoie P (2013) The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? Rev Environ Econ Policy 7(1):2–22
Amiti M, Konings J (2007) Trade liberalization, intermediate inputs, and productivity: evidence from Indonesia. Am Econ Rev 97(5):1611–1638
André FJ, González P, Porteiro N (2009) Strategic quality competition and the Porter hypothesis. J Environ Econ Manag 57(2):182–194
Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev Econ Stud 58(2):277
Arellano M, Bover O (1995) Another look at the instrumental variable estimation of error-components models. J Econom 68(1):29–51
Bandura R (2008) A survey of composite indices measuring country performance: 2008 update. UNDP/ODS working paper, United Nations Development Programme
Barbera AJ, McConnell VD (1990) The impact of environmental regulations on industry productivity: direct and indirect effects. J Environ Econ Manag 18(1):50–65
Bas M, Johansson Å, Murtin F, Nicoletti G (2016) The effects of input tariffs on productivity: panel data evidence for OECD countries. Rev World Econ 152(2):401–424
Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. J Econom 87(1):115–143
Böhringer C, Jochem PE (2007) Measuring the immeasurable? A survey of sustainability indices. Ecol Econ 63(1):1–8
Bourlès R, Cette G, Lopez J, Mairesse J, Nicoletti G (2013) Do product market regulations in upstream sectors curb productivity growth? Panel data evidence for OECD countries. Rev Econ Stat 95(5):1750–1768
Brännlund R, Lundgren T (2009) Environmental policy without costs? A review of the Porter hypothesis. Int Rev Environ Resour Econ 3(2):75–117
Brunel C, Levinson A (2016) Measuring the stringency of environmental regulations. Rev Environ Econ Policy 10(1):47–67
Brunnermeier SB, Cohen MA (2003) Determinants of environmental innovation in US manufacturing industries. J Environ Econ Manag 45(2):278–293
Cagatay S, Mihci H (2006) Degree of environmental stringency and the impact on trade patterns. J Econ Stud 33(1):30–51
Carrión-Flores CE, Innes R (2010) Environmental innovation and environmental performance. J Environ Econ Manag 59(1):27–42
Cohen MA, Tubb A (2018) The impact of environmental regulation on firm and country competitiveness: a meta-analysis of the Porter hypothesis. J Assoc Environ Resour Econ 5(2):371–399
Copeland BR (2011) Trade and the environment. In: Bernhofen D, Falvey RE, Greenaway D, Kreickemeier U (eds) Palgrave handbook of international trade. Palgrave Macmillan, Basingstoke, pp 423–496
Costantini V, Crespi F (2008) Environmental regulation and the export dynamics of energy technologies. Ecol Econ 66(2–3):447–460
Crepon B, Duguet E, Mairessec J (1998) Research, innovation and productivity: an econometric analysis at the firm level. Econ Innov New Technol 7(2):115–158
de Marchi V (2012) Environmental innovation and R&D cooperation: empirical evidence from Spanish manufacturing firms. Res Policy 41(3):614–623
Dechezleprêtre A, Sato M (2017) The impacts of environmental regulations on competitiveness. Rev Environ Econ Policy 11(2):183–206
Delgado M, Ketels C, Porter M, Stern S (2012) The determinants of national competitiveness. National Bureau of Economic Research, Cambridge

Dernis H, Guellec D (2002) Using patent counts for cross-country comparisons of technology output. In: OECD (ed) Special issue on new science and technology indicators, STI review, vol 27, 2001, Paris, pp 129–149

Dufour C, Lanoie P, Patry M (1998) Regulation and productivity. J Prod Anal 9(3):233–247

Erumban AA, Gouma R, de Vries G, de Vries K, Timmer MP (2012) WIOD socio-economic accounts (SEA): sources and methods. http://www.wiod.org/publications. Accessed 13 Feb 2017

Färe R, Grosskopf S, Noh DW, Weber W (2005) Characteristics of a polluting technology: theory and practice. J Econom 126(2):469–492

Franco C, Marin G (2017) The effect of within-sector, upstream and downstream environmental taxes on innovation and productivity. Environ Resour Econ 66(2):261–291

Gerlagh R, Mathys NA, Michielsen TO (2015) Energy abundance, trade and specialization. Energy J 36(3):235–245

Gollop FM, Roberts MJ (1983) Environmental regulations and productivity growth: the case of fossil-fueled electric power generation. J Polit Econ 91(4):654–674

Gray WB (1987) The cost of regulation: OSHA, EPA and the productivity slowdown. Am Econ Rev 77(5):998–1006

Greaker M (2006) Spillovers in the development of new pollution abatement technology: a new look at the Porter-hypothesis. J Environ Econ Manag 52(1):411–420

Griffith R, Redding S, van Reenen J (2004) Mapping the two faces of R&D: productivity growth in a panel of OECD industries. Rev Econ Stat 86(4):883–895

Griliches Z (1990) Patent statistics as economic indicators: a survey. J Econ Lit 28(4):1661–1717

Grossman GM, Helpman E (2001) Innovation and growth in the global economy, 7th edn. The MIT Press, Cambridge (Mass.)

Hamamoto M (2006) Environmental regulation and the productivity of Japanese manufacturing industries. Resour Energy Econ 28(4):299–312

Haščič I, Silva J, Johnstone N (2015) The use of patent statistics for international comparisons and analysis of narrow technological fields, OECD science, technology and industry working papers, vol 2015/05. OECD, Paris

Hellström T (2007) Dimensions of environmentally sustainable innovation: the structure of eco-innovation concepts. Sustain Dev 15(3):148–159

Hille E (2018) Pollution havens: international empirical evidence using a shadow price measure of climate policy stringency. Empir Econ 54(3):1137–1171

Hille E, Shahbaz M (2018) The sources of emission reductions: market and policy-stringency effects. HHL Leipzig Graduate School of Management Working Paper no 172

Holtz-Eakin D, Newey W, Rosen HS (1988) Estimating vector autoregressions with panel data. Econometrica 56(6):1371–1395

Hooghiemstra R (2000) Corporate communication and impression management—new perspectives why companies engage in corporate social reporting. J Bus Ethics 27(1):55–68

Huber PJ (1967) The behavior of maximum likelihood estimates under nonstandard conditions. In: Proceedings of the fifth Berkeley symposium on mathematical statistics and probability, volume 1: statistics, University of California Press, Berkeley, California, pp 221–233

Huhtala A, Marklund PO (2008) Stringency of environmental targets in animal agriculture: shedding light on policy with shadow prices. Eur Rev Agric Econ 35(2):193–217

International Energy Agency (2013) Energy prices and taxes: end-use prices. http://wds.iea.org. Accessed 4 Feb 2013

Jaffe AB, Palmer K (1997) Environmental regulation and innovation: a panel data study. Rev Econ Stat 79(4):610–619

Jaffe AB, Peterson SR, Portney PR (1995) Environmental regulation and the competitiveness of U.S. manufacturing: what does the evidence tell us? J Econ Lit 33(1):132–163

Jaffe AB, Newell RG, Stavins RN (2002) Environmental policy and technological change. Environ Resour Econ 22(1):41–70

Javorcik BS, Wei SJ (2003) Pollution havens and foreign direct investment: dirty secret or popular myth? B E J Econ Anal Policy 3(2):1–34

Jorgenson DW, Griliches Z (1967) The explanation of productivity change. Rev Econ Stud 34(3):249

Kaufmann D, Kraay A, Mastruzzi M (2010) The worldwide governance indicators: methodology and analytical issues (September 2010): World Bank policy research working paper no. 5430

Kneller R, Manderson E (2012) Environmental regulations and innovation activity in UK manufacturing industries. Resour Energy Econ 34(2):211–235

Koźluk T, Zipperer V (2014) Environmental policies and productivity growth : a critical review of empirical findings. OECD J Econ Stud 1:155–185

Lanoie P, Patry M, Lajeunesse R (2008) Environmental regulation and productivity: testing the Porter hypothesis. J Prod Anal 30(2):121–128
Lanoie P, Laurent-Lucchetti J, Johnstone N, Ambec S (2011) Environmental policy, innovation and performance: new insights on the Porter hypothesis. J Econ Manag Strategy 20(3):803–842
Lee KH, Min B (2015) Green R&D for eco-innovation and its impact on carbon emissions and firm performance. J Clean Prod 108:534–542
Levinsohn J, Petrin A (2003) Estimating production functions using inputs to control for unobservables. Rev Econ Stud 70(2):317–341
Lucas RE (1988) On the mechanics of economic development. J Monet Econ 22(1):3–42
Martínez C (2011) Patent families: when do different definitions really matter? Scientometrics 86(1):39–63
Millimet DL, Roy J (2016) Empirical tests of the pollution haven hypothesis when environmental regulation is endogenous. J Appl Econ 31(4):652–677
Mohr RD (2002) Technical change, external economies, and the Porter hypothesis. J Environ Econ Manag 43(1):158–168
OECD (2009) OECD patent statistics manual. OECD, Paris
OECD (2015) Frascati manual 2015: guidelines for collecting and reporting data on research and experimental development–the measurement of scientific, technological and innovation. OECD Publishing, Paris. https://doi.org/10.1787/9789264239012-en
OECD (2017) OECD.Stat. http://stats.oecd.org/. Accessed 20 March 2017
Olley GS, Pakes A (1996) The dynamics of productivity in the telecommunications equipment industry. Econometrica 64(6):1263
O'Mahony M, Timmer MP (2009) Output, input and productivity measures at the industry level: the EU KLEMS database. Econ J 119(538):F374–F403
Palmer K, Oates WE, Portney PR (1995) Tightening environmental standards: the benefit-cost or the no-cost paradigm? J Econ Perspect 9(4):119–132
Porter ME (1991) America's green strategy. Sci Am 264:168–171
Porter ME, van der Linde CM (1995) Toward a new conception of the environment–competitiveness relationship. J Econ Perspect 9(4):97–118
Roodman D (2009) How to do xtabond2: an introduction to difference and system GMM in Stata. Stata J 9(1):86–136 (51)
Rose AK (2004) Do WTO members have more liberal trade policy? J Int Econ 63(2):209–235
Rubashkina Y, Galeotti M, Verdolini E (2015) Environmental regulation and competitiveness: empirical evidence on the Porter hypothesis from European manufacturing sectors. Energy Policy 83:288–300
Sato M, Dechezleprêtre A (2015) Asymmetric industrial energy prices and international trade. Energy Econ 52:S130–S141
Sato M, Neuhoff K, Graichen V, Schumacher K, Matthes F (2015a) Sectors under scrutiny: evaluation of indicators to assess the risk of carbon leakage in the UK and Germany. Environ Resource Econ 60(1):99–124
Sato M, Singer G, Dussaux D, Lovo S (2015b) International and sectoral variation in energy prices 1995–2011: how does it relate to emissions policy stringency? Grantham Research Institute on Climate Change and the Environment. Working paper no. 187
Schmoch U, Laville F, Patel P, Frietsch R (2003) Linking technology areas to industrial sectors: final report to the European Commission, DG Research European Commission. ISI, Karlsruhe
Schreyer P (2001) Measuring productivity: OECD manual—measurement of aggregate and industry-level productivity growth. OECD, Washington
Solow RM (1957) Technical change and the aggregate production function. Rev Econ Stat 39(3):312
Topalova P, Khandelwal A (2011) Trade liberalization and firm productivity: the case of India. Rev Econ Stat 93(3):995–1009
Törnqvist L (1936) The bank of Finland's consumption price index. Bank Finl Month Bull 10:1–8
van Looy B, Vereyen C, Schmoch U (2015) Patent statistics: IPCV8-NACE Rev.2 update (version 2.0). https://circabc.europa.eu. Accessed 23 Jan 2017
van Soest DP, List JA, Jeppesen T (2006) Shadow prices, environmental stringency, and international competitiveness. Eur Econ Rev 50(5):1151–1167
Walker WR (2013) The transitional costs of sectoral reallocation: evidence from the clean air act and the workforce. Q J Econ 128(4):1787–1835
Wang X, Teng F, Zhou S, Cai B (2017) Identifying the industrial sectors at risk of carbon leakage in China. Clim Policy 17(4):443–457
White H (1980) A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48(4):817–830

Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. J Econom 126(1):25–51
World Bank (2017a) World development indicators. http://data.worldbank.org/products/wdi. Accessed 20 March 2017
World Bank (2017b) Worldwide governance indicators. http://info.worldbank.org/governance/wgi. Accessed 20 March 2017
World Input-Output Database (2012a) WIOD environmental accounts: released March 2012. http://www.wiod.org. Accessed 5 Feb 2017
World Input-Output Database (2012b) WIOD national input–output tables: released April 2012. http://www.wiod.org. Accessed 5 Feb 2017
World Input-Output Database (2012c) WIOD socio-economic accounts: released February 2012. http://www.wiod.org. Accessed 5 Feb 2017
Yang CH, Tseng YH, Chen CP (2012) Environmental regulations, induced R&D, and productivity: evidence from Taiwan's manufacturing industries. Resour Energy Econ 34(4):514–532
Young A (2018) Consistency without inference: instrumental variables in practical application. London School of Economics working paper. http://personal.lse.ac.uk/YoungA/. Accessed 10 June 2018