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Environmental regulation and productivity growth: Main policy challenges☆

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ABSTRACT

In this paper, we investigate the environmental regulation-productivity nexus for 18 OECD countries over the years 1990–2015 and discuss its main policy challenges. Our findings support the hypothesis that environmental policies generate positive productivity returns through innovation as suggested by Porter and Van Der Linde (1995). We find that environmental policies have a productivity growth-promoting effect. Both market and non-market based policies exert a positive but differentiated impact both on labour and multifactor productivity growth. As for specific policies, green taxes display the largest effect on multifactor productivity although with potentially negative redistributive effects. We also find that environmental regulation exerts an indirect positive impact on productivity growth fostering capital accumulation especially in high ICT intensive countries.

1. Introduction

The environmental regulation-competitiveness nexus is a significant challenge to policymakers. It became central in the international policy debate especially after the global financial crisis when the so-called "green economy" and "green new deal" paradigms emerged.

The investigation of the mechanisms through which environmental policy affects innovation and productivity, as well as the factors strengthening this relationship, is key to implement compelling policies for environmentally sustainable growth. Actually, in this context, the role of policies is pivotal as both pollution and innovation generate market failures requiring a well-designed public intervention to avoid that firms pollute too much and innovate too little compared to the social optimum. The aim of this paper is to provide a contribution in this respect testing the so called Porter Hypothesis (PH) for 18 OECD countries over the period 1990–2015 and evaluating its main policy challenges. The conventional perception about environmental policy stringency is that it imposes additional costs on firms, which may reduce their global competitiveness thus negatively affecting economic growth and employment. But, at the same time, more tight environmental policies can stimulate innovations that may over-compensate for the costs of complying with these policies (Porter and Van Der Linde, 1995). Following this approach, we test and evaluate three different versions of the PH, namely the

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weak, strong, and narrow (Jaffe and Palmer 1997). The *weak* hypothesis assumes that regulation induces innovation, which in turn stimulates productivity. But this result is not guaranteed as productivity might not improve if the opportunity costs of additional innovation offsets productivity gains. The *strong* version suggests that the benefits from more innovation induced by environmental regulation overcome its costs eventually raising productivity. Finally, the *narrow* hypothesis indicates that, market-based instruments, such as taxes or tradable permits, are more likely to foster innovation and productivity growth as they leave relatively more freedom to the firm in choosing the best technological solution to minimize compliance costs compared to non-marked based instruments.[1]

Existing empirical studies on the relation between environmental regulations and productivity or competitiveness are rather heterogeneous and developed mainly in the context of international trade. Empirical findings are typically very context-specific and focused on diverse indicators of efficiency and innovation (e.g. multifactor productivity, patent counts or efficiency score). As a consequence, the size and the sign of the identified effects are hardly comparable. Only few studies, testing the Porter Hypotheses, documented the impact of more stringent environmental regulation on productivity and environmental innovation adopting a cross-country perspective, but the empirical evidence is inconclusive.[2] Some authors do not find empirical support for the Porter hypotheses. Their argument is that despite improving the environment, stricter environmental policies may imply additional costs for pollution abatement, alter investment decisions, and restrict the availability of inputs for the production process as well as the set of available technologies (Ambec et al., 2013; Ambec and Barla, 2002; Dechezleprêtre and Sato 2017). So, at least in the short-run, higher compliance costs may negatively affect both international competitiveness and productivity growth.

Other research efforts, support the strong Porter hypothesis suggesting that well-designed environmental regulations, along with environmental quality, can improve competitiveness promoting product and process innovation (Ambec and Barla 2002; André et al., 2009). Additionally, Albrizio et al. (2014) indicate that a tightening of environmental policy in the OECD countries is associated to a short-term increase in industry level productivity growth only in the most technologically advanced countries.

Empirical evidence supporting the weak Porter hypothesis, shows that well-designed environmental policy generates positive effects on innovation (Carrión-Flores and Innes 2010; Lanoie et al., 2011), but the impact on productivity growth remains indefinite (Brännlund and Lundgren 2009; Cohen and Tubb 2018). Eventually, other studies find robust support for the strong PH but the results for both weak and narrow PHs remain ambiguous.[3] Martinez Zarzoso et al. (2019), use panel data models and quantile regressions to test the "weak" and "strong" hypotheses, for 18 OECD countries over the years 1990–2011. Consistently with the weak PH, their findings indicate that stringent environmental regulations exert a positive effect on R&D expenditure, the number of patent applications and total factor productivity. De Santis and Jona Lasinio (2016), using a panel data approach for a sample of European countries, found that the "narrow" Porter hypothesis cannot be rejected, and that market based environmental measures are the most suitable instrument to stimulate innovation and productivity growth. Finally, this literature rarely considers the distributive effects of environmental policies that is a substantial matter for policy evaluation (Akshaya et al., 2019).

In this paper, we contribute to existing literature as follows: first, we adopt a country-level analysis to capture the variation both across policies and across outcomes, as well as possible spillover effects. Compared to industry or firm level studies suffering from the lack of generality, a country-level approach is best suited for international policymaking. Second, we disentangle the mediating effect of ICT and non-ICT capital[4] on productivity coherently with both the literature[5] on the key contribution ICT capital to foster productivity growth and with the Porter hypothesis. In this respect, the main assumption for exploring the role of ICT and non-ICT assets separately is that innovative technological investment (ICT) is assumed to be relatively more sensitive to stricter environmental regulation than traditional capital assets (non-ICT). Third, we use a Panel Vector Autoregressive (PVAR) approach to estimate the weak and strong Porter Hypotheses in a single framework. By doing so, we are able to simultaneously assess the direct and indirect impact of environmental policy on productivity evaluating also the effect of technology adoption through capital accumulation. Finally, to explore more deeply the role of ICT capital we estimate direct and mediated effects of EPS separately for high and low ICT-intensive countries.

Our findings support the assumption that environmental policies in OECD countries had a growth-promoting effect on productivity (strong PH hypothesis validated). Compared to the recent literature finding mixed empirical evidence, this result corroborates the relevance of aggregate analyses to take into account cross sectional heterogeneity and spillover effects. We find that productivity increases resulting from changes in the environmental regulation pass through a stimulus to capital accumulation and that this effect is concentrated in high ICT intensive countries (weak PH hypothesis validated). We provide evidence that both market and non-marked based policies exert a positive impact on productivity although with potentially heterogeneous redistributive effects (narrow PH hypothesis ambiguous).

The paper is organized as follows: section II describes the data and shows some descriptive evidence while section III illustrates the empirical strategy. Sections IV and V show estimation results and robustness checks and section VI concludes.

[1] The correlation of environmental stringency indicator with green patents is significantly higher for the market-based component, which maybe a sign of the higher effectiveness of market-based instruments to stimulate "green" innovation (as in Johnstone et al., 2010; OECD, 2010). See also Fischer et al. (2003), Jaffe and Palmer (1997).

[2] For a recent survey see Martinez Zarzoso et al., (2019).

[3] See for example Ambec et al., 2013; Franco and Marin (2017) and Yang et al., (2012).

[4] Information and Communication Technologies include software, hardware and communication equipment while non-ICT refers to traditional assets such as machinery and equipment, structures and buildings (OECD, 2002).

[5] See Jorgenson and Vu (2005).

2. Data and descriptive statistics

Our analysis covers 18 OECD economies (Austria – Aut., Canada – Can., Czech republic – Cze., Denmark – Dnk., Finland – Fin., France – Fra., Germany – Deu., Greece – Gre., Hungary – Hun., Italy – Ita., Poland – Pol., Portugal – Por., Spain – Esp., Slovakia – Svk., Sweden – Swn., The Netherlands – Ndl., Great Britain – Grb. and USA).[6] The country selection has been partly constrained by data availability, so that our sample economies have been selected among those that have followed the OECD environmental guidelines relatively closely and for which data on different asset types are available(see Tables A1 and A2 in the appendix). Notice that the OECD has been very active in the design of effective environmental regulation policies since the beginning of the 1970s.[7]

In this paper we focus on productivity[8] and test environmental adjusted productivity indicators accounting for the use of natural capital (currently including 14 types of fossil fuels and minerals) and for the emission of pollutants as negative by-products (currently including 8 types of greenhouse gases and air pollutants). We measure environmental adjusted labor productivity as environmental adjusted GDP for pollution abatement in per hour terms. The adjustment approach take into account country's technological capabilities (e.g. innovative ways to abate pollution) and changes in economic structure (e.g. less emission-intensive industries)[9].

To investigate the Environmental regulation-productivity nexus we use the Environmental Policy Stringency (EPS)[10] composite index, developed for the OECD countries by Botta and Koźluk (2014). The EPS index is well suited for testing the narrow Porter Hypothesis as it distinguishes between: i) market-based instruments providing market incentives to the reduction or removal of negative environmental externalities and ii) non market based instruments that are mostly regulatory provisions.

The dynamics of EPS indicate a tightening trend both at the aggregate level and individually across countries since the beginning of the 90s. At the same time, dispersion increased across countries (Fig. 1).[11]

Over the past two decades, there has been an extension of the number of market-based policy instruments (i.e. the emission trading system in EU countries in 2005) (see Fig. A1 in the appendix) as opposed to the non-market-based that remained the same just becoming more stringent compared to the 1990s.

3. Econometric model and strategy

To test the Porter Hypotheses (PH), we use a Panel VAR (PVAR) approach consisting in a system of equations where each variable is expressed as a dynamic function of lagged values of (endogenous) variables. PVAR, alongside single equation GMM-based dynamic panels, became standard in the estimation of production function coefficients as it controls for reverse causality and simultaneity bias. These endogeneity issues are typical features of production functions where inputs are jointly determined with output. As for the relation between Environmental policy stringency index (EPS) and productivity, endogeneity issues might be the result of measurement errors and unobserved components affecting both environmental regulation and productivity growth (Mobius, 2018).

The Panel VAR representation as a system of equations is as follows:

$$\Delta Prod_{i,t}^{k} = \beta_0 \Delta Prod_{i,t-1} + \beta_1 \Delta kict_{i,t-1} + \beta_2 \Delta knoict_{i,t-1} + \beta_3 \Delta EPSI_{i,t-1}^{j} + \varepsilon_{i,t}^{1} \tag{1a}$$

$$\Delta knoict_{i,t} = \beta_4 \Delta Prod_{i,t-1}^{k} + \beta_5 \Delta kict_{i,t-1} + \beta_6 \Delta knoict_{i,t-1} + \beta_7 \Delta EPSI_{i,t-1}^{j} + \varepsilon_{i,t}^{2} \tag{1b}$$

$$\Delta kict_{i,t} = \beta_8 \Delta Prod_{i,t-1}^{k} + \beta_9 \Delta kict_{i,t-1} + \beta_{10} \Delta knoict_{i,t-1} + \beta_{11} \Delta EPSI_{i,t-1}^{j} + \varepsilon_{i,t}^{3} \tag{1c}$$

$$\Delta EPSI_{i,t} = \beta_8 \Delta Prod_{i,t-1}^{k} + \beta_{13} \Delta kict_{i,t-1} + \beta_{14} \Delta knoict_{i,t-1} + \beta_{15} \Delta EPSI_{i,t-1}^{j} + \varepsilon_{i,t}^{4} \tag{1d}$$

[6] In our estimates we integrated OECD data with EUKLEMS data. Unfortunately, data for Australia, Japan and Korea (as well as Norway, New Zealand and the BRICs and others) are not available in any of the two datasets.

[7] The OECD strongly supported the achievement of the two United Nations climate treaties. The OECD was also among the main promoters of the Paris Agreement at the COP21 in Paris, which went into force in November of 2016.

[8] Other studies have analyzed the effects of environmental regulation on several different measures of competitiveness (i.e. impacts on business performance, trade flows, FDI, and employment).

[9] Traditional indicators are biased in two ways. First, while income generated with domestic natural assets is fully reflected, no account is taken of the natural resource input (in terms of the resource rents). Increased natural resource use is therefore wrongly interpreted as a rise in productivity. Second, while the costs of investing in pollution abatement are fully captured (in terms of factor inputs including labour and produced capital), no account is taken of the benefits of such investments because pollution is not considered as an output of the production process. Increased abatement efforts therefore make productivity appear falsely low. (See Brandt et al, 2013, 2014).

[10] The EPS covers 24 OECD countries over the period 1990–2015. The indicator is based on the taxonomy developed by De Serres et al. (2010) and the sub-components are all weighted equally. A market-based subcomponent groups instruments, which assign an explicit price to the externalities (taxes: CO2, SOX, NOX, and diesel fuel; trading schemes: CO2, renewable energy certificates, energy efficiency certificates; feed in-tariffs; and deposit-refund-schemes), while the non-market component clusters command-and-control instruments, such as standards (emission limit values for NOX, SOX, and PM, limits on Sulphur content in diesel), and technology-support policies, such as government R&D subsidies.

[11] For the period 2008–2015 three country groups can be distinguished with regard to their aggregate regulatory stance, although incremental differences are relatively small (Fig. 1): at the lower end of the spectrum, Greece, Italy, Portugal an USA; in the middle Germany, Great Britain, Austria and Sweden and with the highest regulatory stance Finland, France, Canada, the Netherland and Denmark.

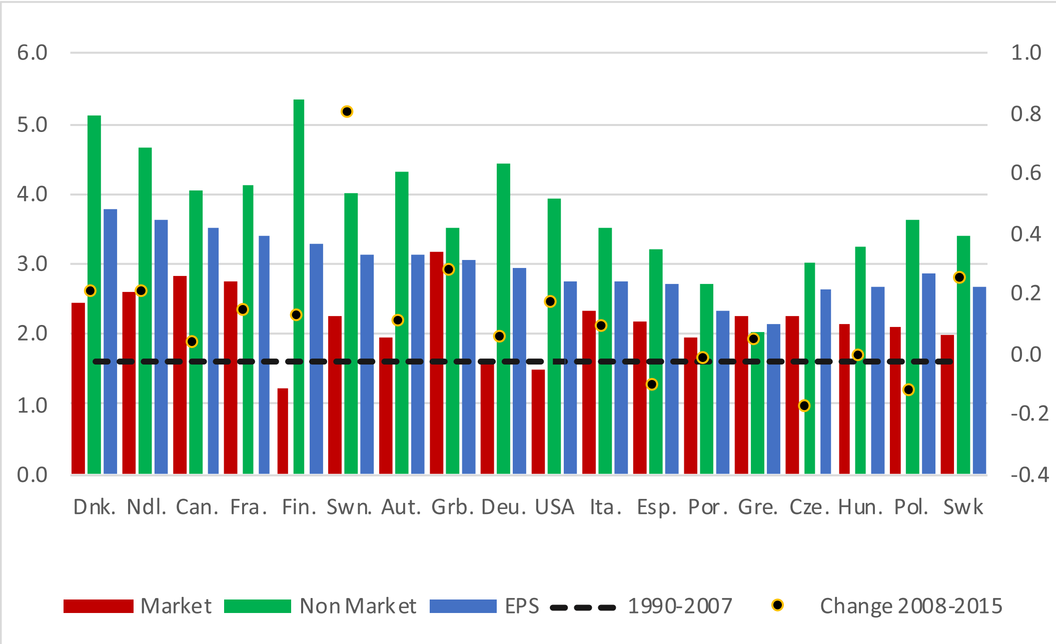

Fig. 1. Environmental policy index 2008–2015.
Source: OECD.Stat

where *Prod* refers to the log of two different (k = 2) productivity indicators: environmentally adjusted labour productivity (output per hour worked, *HLP*); and environmentally adjusted multifactor productivity (*MFP*);

As for the regressors, *kict* is the log-stock of ICT capital and *knoict* is the log-stock of non-ICT capital per hour worked at constant prices. EPS^j is our environmental policy indicator, with j = total EPS index (EPSI); Market Based EPS (EPSMKT); Non-Market Based EPS (EPSNMKT); taxes (TAX); Feed in tariffs (FIT); R&D Subsidies (RDS); Standards (STD); and Trading Schemes (TRS).

The choice of estimating a system of equation in first differences is related to the availability of environmentally adjusted productivity indicators only in growth rates. As shown in Table A3 in the appendix, according to the Im et al. (2003) test, these variables are stationary, while the two measures of capital intensity and the EPS index are stationary in first differences only.[12] Hence, a long-run representation including one or more cointegration vectors is not allowed and the short-run representation must be estimated in first differences.

The Panel VAR system of equations (1a)-(1d) is estimated with a GMM approach where endogenous variables are instrumented with their first three lags to ensure that for each equation the number of instruments does not exceed the number of panels. The validity of overidentifying restrictions will be tested using the Hansen J statistic.[13] Regression coefficients estimated through GMM are unbiased and consistent, however, they only show simultaneous impacts. In order to better explore the mechanism through which environmental policy affects capital accumulation and productivity over time, we calculate orthogonal impulse-response functions (IRF). The identification strategy assumes that environmental policy is an exogenous variable determined by policymakers. We use a Cholesky decomposition whereby a shock in EPS affects capital stocks and productivity with a lag. The actual impact will be then assessed via a forecast error variance decomposition showing the share of the variability of dependent variables explained by a standard deviation change in each EPSI.

4. Regressions results

Table 1 show the results for the productivity equation (1a) using total EPS index (EPSI), Market Based EPS (EPSMKT) and Non-Market Based EPS (EPSNMKT) as measures of policy environmental stringency. The results for equations (1b)-(1d) are shown in Table A4 in the Appendix. The good performance of the GMM estimator is corroborated by the Hansen J statistics confirming the validity of overidentifying restrictions.

The results support the validity of the augmented production function estimates: both ICT and non- ICT capital intensity coefficients

[12] The null assumption in the test is that all series have a unit root whereas the alternative assumption is that a non-zero fraction on panels is stationary. Compared to other unit root test for panel data, the procedure is robust to the presence of cross-sectional dependence.

[13] The estimation procedure transforms variables in forward orthogonal deviation to eliminate fixed effects and removes cross sectional dependence (CSD) by using cross sectional averages of all variables.

Table 1
Estimation results for equation (1a).

	Multifactor Productivity (MFP)				Hourly Labour Productivity (HLP)			
	1	2	3	4	5	6	7	8
$\Delta prod_{t-1}$	0.590***	0.622***	0.945***	0.570***	0.528***	0.614***	0.652***	0.491***
	[0.073]	[0.069]	[0.111]	[0.080]	[0.082]	[0.079]	[0.109]	[0.096]
$\Delta knoict_{t-1}$	0.236***	0.270***	0.024	0.255***	0.150***	0.186***	0.019	0.268***
	[0.050]	[0.050]	[0.077]	[0.061]	[0.037]	[0.035]	[0.051]	[0.055]
$\Delta kict_{t-1}$	0.019**	0.027**	0.019**	0.021**	0.014**	0.016**	0.005	0.004
	[0.007]	[0.009]	[0.008]	[0.009]	[0.007]	[0.006]	[0.007]	[0.010]
$\Delta EPSI_{t-1}$	0.013***				0.011**			
	[0.003]				[0.004]			
$\Delta EPSMKT_{t-1}$		0.009**	0.009**			0.007**	0.008**	
		[0.003]	[0.004]			[0.003]	[0.003]	
$\Delta EPSNMKT_{t-1}$		0.003		0.004**		0.003*		0.004**
		[0.002]		[0.002]		[0.002]		[0.002]
Hansen	59.5	82.8	17.5	49.4	53.6	80.9	12.6	45.1
pval	0.112	0.251	0.35	0.416	0.297	0.298	0.701	0.591
N	288	288	288	288	288	288	288	288

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level. EPS = environmental protection stringency; averages; EPSMKT = market based EPS index; EPSNMKT = non-market based EPS index; kict = log-ICT capital per hour worked; knoict = log non-ICT capital per hour worked. Source: own estimates on OECD data.

are positive and significant, coherently with the empirical literature in the field (Spiezia, 2012; Timmer et al., 2010; Corrado et al., 2017).

The EPSI coefficient is positive and significant for both productivity measures, coherently with the assumptions of the Strong Porter hypothesis. The decomposition between market and non-market based policies suggests that the former play a larger role in accelerating (both multifactor and hourly labour) productivity dynamics. This finding supports the Narrow Porter Hypothesis and shows that non-market-based policies are important too.

A deeper analysis of the contribution of ICT capital is provided in Table 2 showing the Panel VAR estimates of equation (1a) testing the effect of EPS independently for high and low ICT-intensive countries. We identify two main group of countries according to the average level of ICT capital per hour worked: high ICT intensive countries are those with above average ICT intensity while the remaining countries are classified as low ICT intensive.[14] Our findings are coherent with (Albrizio et al. (2014)) and support our initial

Table 2
Panel VAR estimates for equation (2a): testing EPS in high and low ICT intensive countries.

	MFP			HLP		
	EPSI	EPSMKT	EPSNMKT	EPSI	EPSMKT	EPSNMKT
	1	2	3	4	5	6
$\Delta prod_{t-1}$	0.662***	0.595***	0.630***	0.629***	0.544***	0.586***
	[0.069]	[0.074]	[0.078]	[0.079]	[0.090]	[0.093]
$\Delta knoict_{t-1}$	0.260***	0.243***	0.168***	0.142***	0.123**	0.086**
	[0.045]	[0.057]	[0.045]	[0.036]	[0.041]	[0.038]
$\Delta kict_{t-1}$	0.024***	0.016*	0.013**	0.015**	0.011*	0.008
	[0.006]	[0.008]	[0.006]	[0.007]	[0.006]	[0.006]
$\Delta EPSIhi_{t-1}$	0.018***	0.011**	0.008**	0.017***	0.011**	0.007**
	[0.005]	[0.004]	[0.003]	[0.005]	[0.004]	[0.003]
$\Delta EPSIlow_{t-1}$	0.010**	0.008**	−0.003	0.003	0.002	−0.001
	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Hansen J	61.8	57.6	47.2	55.2	57.1	46.8
p-value	0.122	0.258	0.584	0.284	0.261	0.615
N	288	288	288	288	288	288

* significant at 10% level; **significant at 5% level; ***significant at 1% level. EPS = environmental protection stringency; averages; EPSIhi = EPSI in ICT intensive countries; EPSIlow = EPS in low-ict intensive countries; kict = log-ICT capital per hour worked; knoict = log non-ICT capital per hour worked. Source: own estimates on OECD data.

[14] High ICT capital countries are Austria, Germany, Denmark, Finland, France, the Netherlands and Sweden; low ICT capital countries are Canada, Spain, UK, Greece, Italy, Portugal, USA, Czech Republic, Hungary, Poland and Slovakia. The dichotomization of the impact allows to avoid the introduction of non-linear terms (i.e. the interaction between EPS and ICT levels) and maintain the methodology simple and intuitive. Cross validation analyses (available upon request) show that estimated coefficients are mostly insensitive to group switches of countries close to the average value.

assumptions: EPS is positive and significant in high ICT intensive countries. In this group, both market-based and non-market-based policies exert positive and significant impacts on both productivity indicators. In low-ICT intensive countries, on the other hand, EPS contributes explaining just multifactor productivity driven by market-based measures. Overall, these findings suggest that ICT capital is a strategic factor for exploiting productivity gains under stricter environmental regulations. This can be considered an alternative approach to test the weak PH whereby the focus is on technology adoption via capital accumulation rather than on innovation activities such as R&D expenditure and patents.

In Table 3, we estimate separately the influence of each policy measure. These results indicate that the most effective measure in fostering productivity is the use of emission trading schemes (columns 5 and 10). In addition, standards and feed-in tariffs affect positively multifactor productivity whereas R&D subsidies seem to positively but weakly contributing to hourly labour productivity growth.

In Table 4 we distinguish the impact of each policy measure for high and low ICT intensive countries. The effect of trading schemes is positive in both groups although the significance is bigger for high-ICT intensive countries. In this group, standards and R&D subsidies exert a significant impact on both productivity indicators (columns 3, 4, 8 and 9). The significant effect of feed-in tariffs on multifactor productivity seems to vanish when we split the sample, while a moderately positive effect of taxes on MFP emerges for low ICT intensive countries.

We found the following: i) environmental policy stringency has a positive and significant impact on productivity, thus confirming the Strong PH; ii) the effect is larger in high-ICT intensive countries, confirming the Weak PH based on capital accumulation and technology adoption; iii) market-based policies seem to play – on average - the main role in fostering productivity improvements, in line with the Narrow PH; iv) the Narrow PH holds mostly for low-ICT intensive countries, whereas in high-ICT intensive countries, the use of trading schemes together with non-market based policies look as the most effective policy mix.

5. Impulse-response analysis and forecast error variance decomposition

Panel VAR coefficients do not properly account for the impact of an exogenous shock on EPS. They represent the impact in t+1 of a shock in t but do not capture the persistence of the shock and the feedback loops from the other variables. To get a reliable measure for the effect of EPS on productivity, we need to estimate orthogonal impulse response functions, calculated using a Cholesky decomposition. To identify exogenous shock in EPS we impose the following ordering of variables: EPS → Kict→Knoict→Prod. This means that a shock in EPS in a specific period will affect the other variables instantaneously, whereas a shock to the other regressors will affect EPS with a delay of 1 year.

In Fig. 2, we show the responses of MFP, *kict* and *knoict* to a shock to EPS (left panels) and to the two components of market based and non-marked based measures (right panels). The results are coherent with the estimated coefficients showing that a shock in EPS affects productivity with a time lag. The effect remains positive in the second and third period but fades to zero in the following periods. We also find a positive effects of EPS on *kict* and, to a lower extent, on *knoict*, with the former driven by non-market-based measures and the latter driven by market-based measures.

Fig. 3 shows the same responses for the specification for hourly labour productivity. The results are substantially unchanged.

Fig. 4 shows the responses of productivity, *kict* and *knoict* when EPS impacts are tested separately for high-ICT-intensive and low-ICT-intensive countries. The results confirm previously estimated coefficients: the response of multifactor productivity to a shock in EPS is stronger in high-ICT intensive countries and both market and non-market-based measure contribute to the result; in low-ICT intensive countries, the impact over time is lower and driven by market-based measures only. The response of ICT capital to a shock in EPS is also stronger in high-ICT intensive countries and the effect is driven by non-market based measures.

The same is found for hourly labour productivity (Fig. 5) with EPS exerting a positive effect over time in high-ICT intensive countries only. Finally, to assess the actual contribution of a shock in EPS to productivity and capital accumulation, Table 5 shows the forecast error variance decomposition after ten periods. Overall, a shock in the EPS explains between 2.5% and 2.9% (columns 1 and 4) of the total variability in productivity after 10 periods. The impact increases to 3.7%–3.8% in high-ICT intensive countries and to 3.1%–3.6% when market-based measures are considered.[15]

As for the effects on capital accumulation, they range between 1.3% and 1.7% in high-ICT-intensive countries while being below 1% in low-ICT intensive countries (Table 3). Coherently with the previous findings, non-market-based measures effects are relatively stronger capital accumulation in high-ICT intensive countries in MFP specifications: a standard deviation increase in non-market-based EPS makes ICT capital intensity raise by 1.5% and non-ICT capital intensity by 1%. Summing up, the impulse response analysis supports the results of the previous section and adds important insights on indirect effects of changes in the EPS and its main components. More specifically, we find that an increase in the stringency of environmental policy makes ICT capital accumulation increasing. In this respect, non-market measures, as standards and R&D subsidies, appear as the most effective policy instruments.

6. Conclusions

In this paper we assessed the role of environmental policy stringency on environmentally adjusted productivity measures for a

[15] As robustness check, we show the error variance of productivity explained by EPS for different ordering of variables in the Cholesky decomposition (Figure A2 in the appendix). Figures show that the main results hold and when the EPS is not the first variable to be shocked the response might increase up to 3.5%–4.5%.

Table 3
Panel VAR estimates for equation (1a): effect of the different policy measures.

	MFP					HLP				
	1	2	3	4	5	6	7	8	9	10
$\Delta prod_{t\text{-}1}$	0.622***	0.453***	0.460***	0.833***	0.388***	0.433***	0.194	0.405***	0.647***	0.539***
	[0.068]	[0.089]	[0.092]	[0.075]	[0.061]	[0.082]	[0.118]	[0.097]	[0.097]	[0.090]
$\Delta knoict_{t\text{-}1}$	0.149**	0.162**	0.250***	0.045	0.092**	0.127***	0.242***	0.186**	0.070*	0.226***
	[0.046]	[0.058]	[0.070]	[0.042]	[0.045]	[0.038]	[0.070]	[0.061]	[0.041]	[0.049]
$\Delta kict_{t\text{-}1}$	0.016**	0.018**	0.023**	0.022***	0.062**	0.019**	0.017	0.008	0.015**	0.032**
	[0.006]	[0.008]	[0.011]	[0.007]	[0.020]	[0.007]	[0.011]	[0.010]	[0.007]	[0.010]
$\Delta TAX_{t\text{-}1}$	0.000					0.002				
	[0.006]					[0.005]				
$\Delta FIT_{t\text{-}1}$		0.004**					0.000			
		[0.002]					[0.001]			
$\Delta RDS_{t\text{-}1}$			0.002					0.003*		
			[0.002]					[0.001]		
$\Delta STD_{t\text{-}1}$				0.004**					0.002	
				[0.001]					[0.001]	
$\Delta TRS_{t\text{-}1}$					0.004***					0.005***
					[0.001]					[0.001]
Hansen J	55.1	37.8	42.5	55.5	54.9	50.5	62.5	46.9	51.1	79.7
p-value	0.223	0.855	0.696	0.213	0.247	0.376	0.528	0.518	0.353	0.003
N	288	288	288	288	288	288	288	288	288	288

* significant at 10% level; **significant at 5% level; ***significant at 1% level. kict = log-ICT capital per hour worked; knoict = log non-ICT capital per hour worked. TAX = taxes; FIT = feed in tariffs; RDS = R&D subsidies; STD = standards; TRS = trading schemes. Source: own estimates on OECD data.

Table 4
Panel VAR estimates for equation (2a): effect of the different policy measures for high and low ICT intensive countries.

	MFP					HLP				
	1	2	3	4	5	6	7	8	9	10
$\Delta prod_{t\text{-}1}$	0.601***	0.519***	0.450***	0.732***	0.328***	0.498***	0.453***	0.057	0.603***	0.519***
	[0.070]	[0.071]	[0.081]	[0.066]	[0.052]	[0.072]	[0.083]	[0.107]	[0.084]	[0.077]
$\Delta knoict_{t\text{-}1}$	0.146***	0.143***	0.254***	0.154***	0.267***	0.097**	0.194***	0.222**	0.141***	0.308***
	[0.042]	[0.043]	[0.056]	[0.042]	[0.056]	[0.036]	[0.046]	[0.073]	[0.037]	[0.051]
$\Delta kict_{t\text{-}1}$	0.021***	0.023	0.016*	0.024***	0.057***	0.022**	0.005	0.019*	0.018**	0.028**
	[0.005]	[0.017]	[0.008]	[0.006]	[0.016]	[0.007]	[0.018]	[0.010]	[0.007]	[0.009]
$\Delta TAXhi_{t\text{-}1}$	−0.009					0.003				
	[0.008]					[0.007]				
$\Delta TAXlow_{t\text{-}1}$	0.008*					0.005				
	[0.004]					[0.005]				
$\Delta FIThi_{t\text{-}1}$		0.003*					0.002			
		[0.002]					[0.002]			
$\Delta FITlow_{t\text{-}1}$		0.003					0.001			
		[0.002]					[0.002]			
$\Delta RDShi_{t\text{-}1}$			0.005**					0.004**		
			[0.002]					[0.002]		
$\Delta RDSlow_{t\text{-}1}$			−0.002					0.000		
			[0.002]					[0.002]		
$\Delta STDhi_{t\text{-}1}$				0.005**					0.004**	
				[0.002]					[0.002]	
$\Delta STDlow_{t\text{-}1}$				−0.001					−0.001	
				[0.002]					[0.002]	
$\Delta TSChi_{t\text{-}1}$					0.004***					0.006***
					[0.001]					[0.001]
$\Delta TRSlow_{t\text{-}1}$					0.004*					0.007***
					[0.002]					[0.002]
Hansen J	88.4	88.2	80.5	83.2	80.9	81.9	78.8	80.9	91.4	82.8
p-value	0.137	0.141	0.312	0.243	0.303	0.273	0.359	0.301	0.095	0.253
N	288	288	288	288	288	288	288	288	288	288

* significant at 10% level; **significant at 5% level; ***significant at 1% level. kict = log-ICT capital per hour worked; knoict = log non-ICT capital per hour worked. TAX = taxes; FIT = feed in tariffs; RDS = R&D subsidies; STD = standards; TRS = trading schemes. Source: own estimates on OECD data.

sample of 18 OECD countries between 1990 and 2015. We empirically tested the Strong and Narrow versions of the Porter hypothesis. Our findings suggest that the need to speed up the transition towards a "green economy" for environmental protection purposes can be seen also as an opportunity to improve productivity and economic growth.

Our results indicate that the Strong Porter hypothesis cannot be rejected. Indeed, environmental policies have a productivity growth-

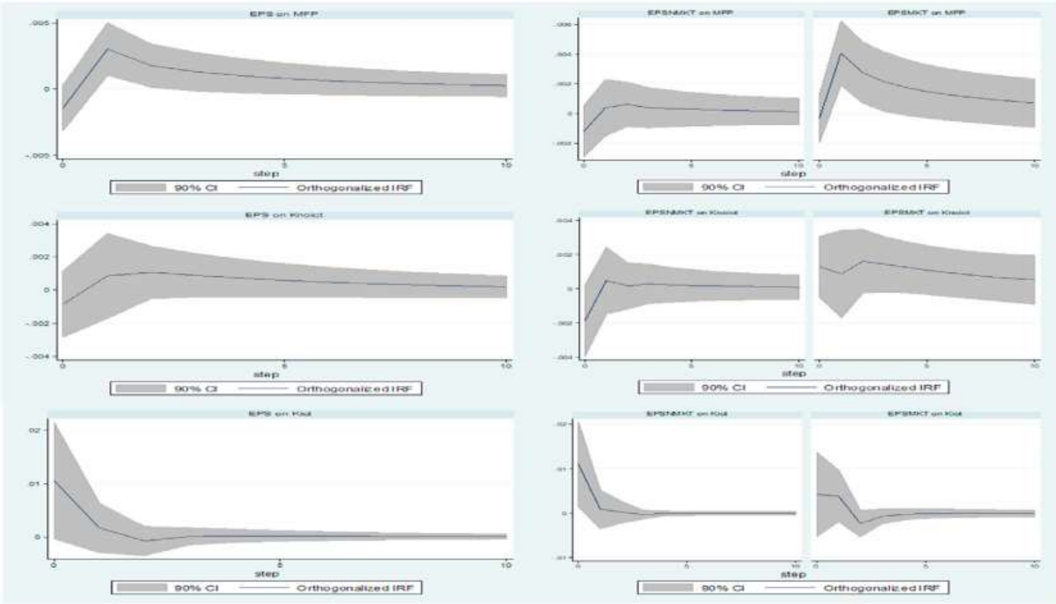

Fig. 2. Orthogonalized Impulse Response Functions: specification with Multifactor productivity.

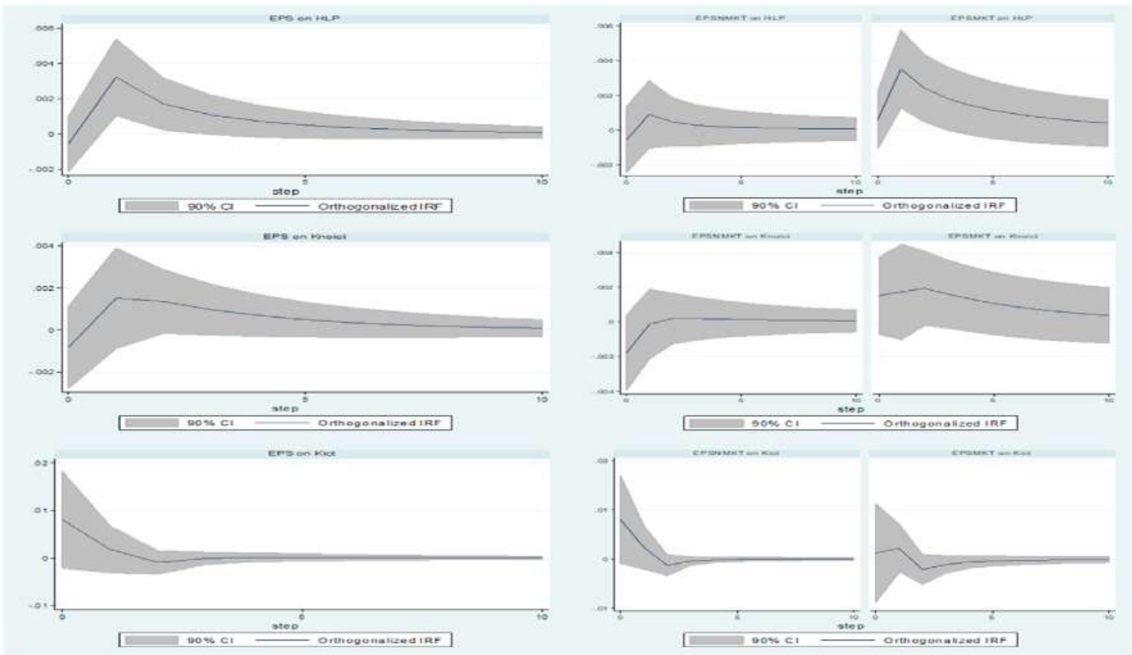

Fig. 3. Orthogonalized Impulse Response Functions: specification with Hourly Labour Productivity.

promoting effect. Moreover, on average it seems that market-based policies contribute mainly to productivity growth, coherently with the Narrow Porter Hypothesis especially for low-ICT intensive OECD countries, where taxes and trading schemes are the main drivers of productivity growth.

In high-ICT countries, alongside the highly significant impact of trading schemes, non-market-based policies (i.e. R&D subsidies and Standards) play a dual role: they contribute directly to productivity increase but they provide also an indirect contribution to productivity by stimulating capital accumulation in the ICT sector. This is coherent with the assumptions of the Strong Porter Hypothesis that investment in high tech capital allows countries to better exploit the innovations opportunities provided by different stringency level environmental policies.

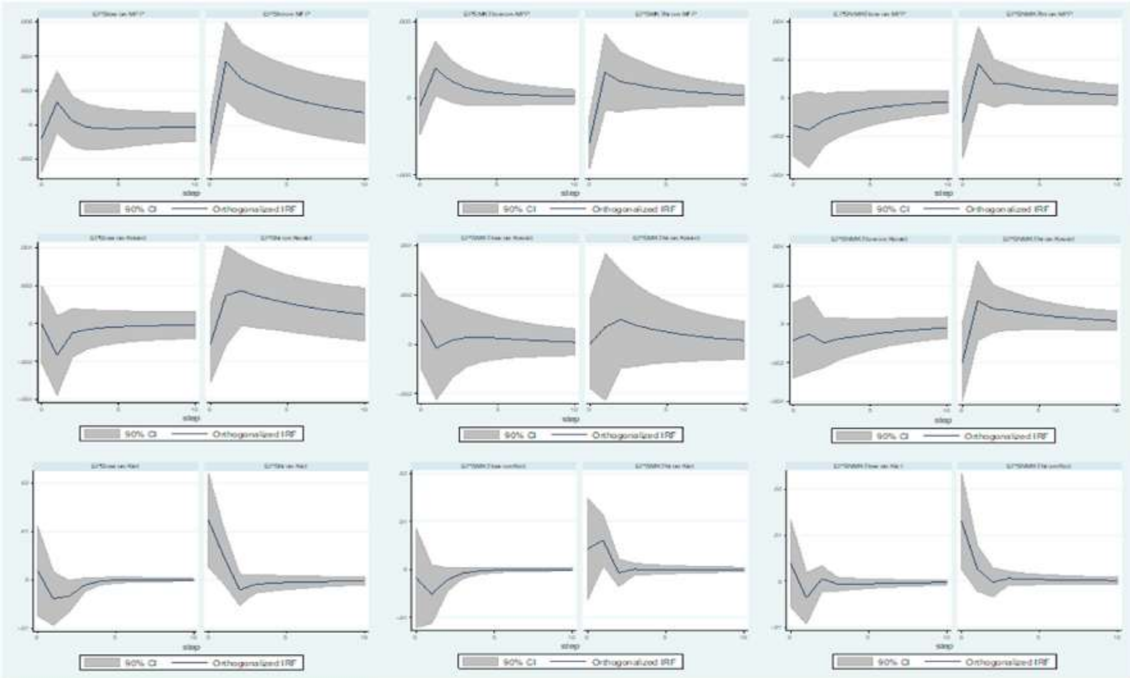

Fig. 4. Orthogonalized Impulse Response Functions: specification with Multifactor Productivity: high and low ict intensive countries.

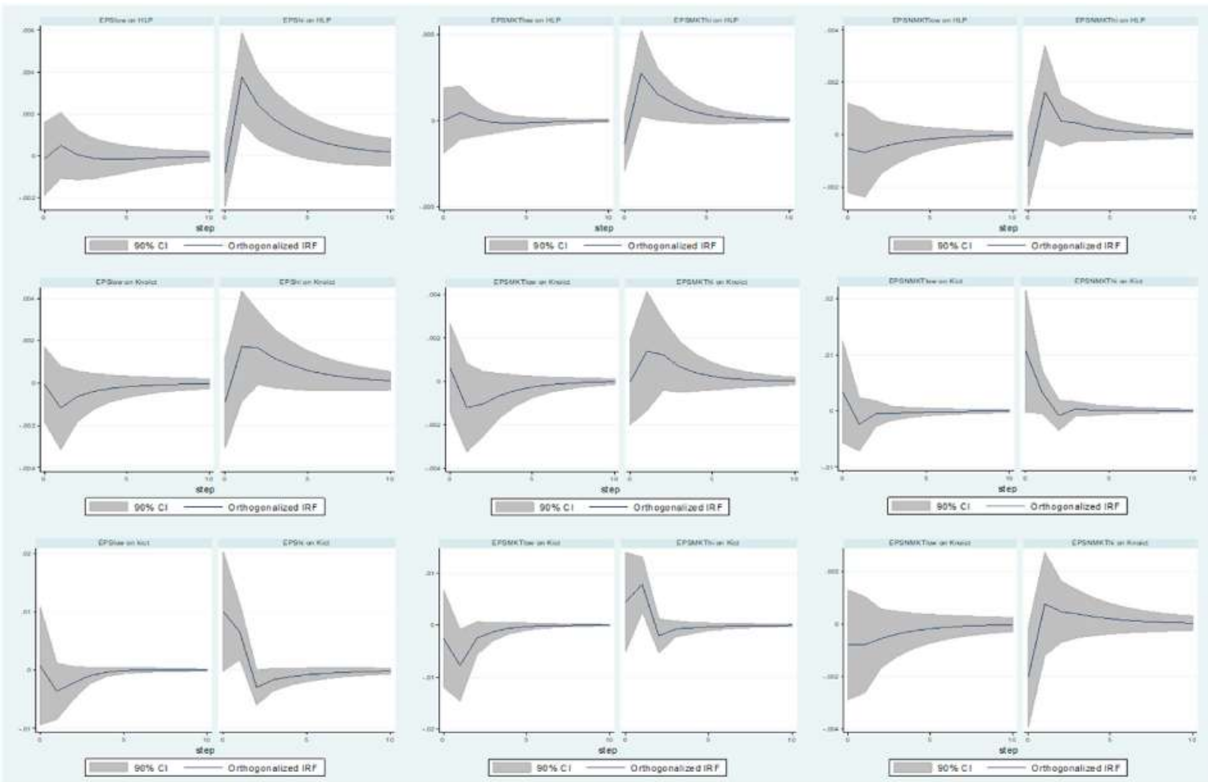

Fig. 5. Orthogonalized Impulse Response Functions: specification with Hourly Labour Productivity: high and low ict intensive countries.

Table 5
Forecast Error Variance Decompostion after 10 periods

	Specification with MFP			Specification with HLP		
	MFP	KICT	KNOICT	HLP	KICT	KNOICT
EPS	0.025	0.010	0.007	0.029	0.006	0.009
EPSIhi	0.037	0.015	0.017	0.038	0.014	0.013
EPSIlow	0.003	0.003	0.004	0.001	0.002	0.003
EPSMKT	0.036	0.003	0.014	0.031	0.001	0.016
EPSNMKT	0.002	0.011	0.004	0.002	0.007	0.004
EPSMKThi	0.025	0.005	0.004	0.027	0.008	0.006
EPSMKTlow	0.008	0.003	0.002	0.001	0.007	0.005
EPSNMKThi	0.010	0.015	0.009	0.010	0.011	0.007
EPSNMKTlow	0.011	0.002	0.004	0.002	0.002	0.003

Note: the table show the percentange of the standard deviation of each variable explained by a standard deviation increase in the EPS. EPSIhi/EPSIlow = EPS in high and low ICT intensive countries. EPSMKT/EPSNMKT = market-based and non-market based EPS.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.inteco.2021.01.002.

Appendix

Table A1
Data description

Variable	Description	Source
HLP ea	Environmentally adjusted hourly labour productivity growth: growth of environmentally adjusted GDP minus growth of total hours worked (in logs)	OECD
MFP	Environmentally adjusted multifactor productivity growth	OECD
kict	ICT capital stock per hour worked (in logs)	OECD, EUKLEMS
knoict	Non-ICT capital stock per hour worked (in logs)	OECD, EUKLEMS
EPSI	Environmental Policy Stringency Index	OECD
EPSMKT	Market-based Environmental Policy Stringency index	OECD
EPSNMKT	Non Market-based Environmental Policy Stringency index	OECD
TAX	Environmental Policy Stringency Index: Taxation policy	OECD
FIT	Environmental Policy Stringency Index: Feed in tariffs policy	OECD
RDS	Environmental Policy Stringency Index: R&D subsidies policy	OECD
STD	Environmental Policy Stringency Index: Standards policy	OECD
TS	Environmental Policy Stringency Index: Trading Schemes policy	OECD

Table A2
Descriptive statistics

	mean	s.d.	min	Max
Δmfp	0.014	0.022	−0.093	0.114
Δhlp	0.021	0.022	−0.083	0.110
Δkict	0.041	0.035	−0.103	0.259
Δknoict	0.054	0.105	−0.886	0.465
ΔEPS	0.101	0.299	−0.633	1.113
ΔEPSMKT	0.071	0.391	−1.167	2.083
ΔEPSNMKT	0.132	0.442	−1.000	1.875
ΔTAX	0.020	0.254	−1.000	1.500
ΔRDS	0.066	0.690	−2.000	3.000
ΔSTD	0.197	0.560	0.000	3.500
ΔFIT	0.110	0.948	−4.000	5.500
ΔTRS	0.085	0.776	−2.000	2.600

Source: own elaboration on OECD.Stat, EUKLEMS.

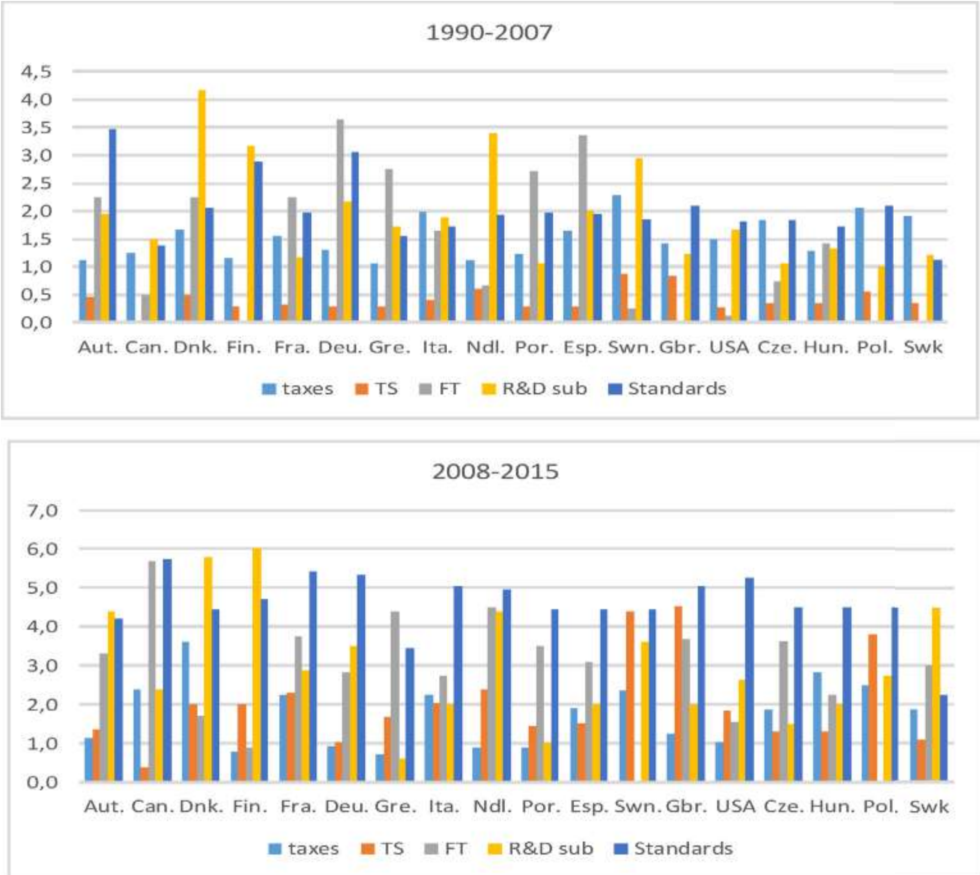

Fig. A1. EPS sub-components. Source: OECD.Stat

Table A3
Unit Root tests

	levels, 1 lag	levels, 2 lags	1st differences, 1 lag	1st differences, 2 lags
MFP			−4.73***	−1.74**
HLP			−4.28***	−1.91**
EPSI	0.63	0.43	−7.87***	−4.71***
kict	−0.35	−0.38	−9.19***	−4.04***
knoict	−2.26**	−1.03	−3.45***	−2.05**

*significant at 10% level; **significant at 5% level; ***significant at 1% level. Note: Im et al. (2003), null assumptions: all series have a unit root. Alternative assumption: some series are stationary.

Table A4
Estimation results for equations (1b)-(1d).

	MFP			HLP		
Eq (1b)	EPSI	EPSMKT	EPSNMKT	EPSI	EPSMKT	EPSNMKT
	1	2	3	4	5	6
$\Delta prod_{t-1}$	0.227**	−0.008	0.236**	0.229**	−0.119	0.224**
	[0.080]	[0.095]	[0.078]	[0.095]	[0.115]	[0.094]
$\Delta knoict_{t-1}$	0.468***	0.558***	0.512***	0.451***	0.570***	0.520***
	[0.067]	[0.073]	[0.069]	[0.067]	[0.079]	[0.066]
$\Delta kict_{t-1}$	0.036***	0.037***	0.040***	0.033***	0.040***	0.037***
	[0.008]	[0.008]	[0.009]	[0.008]	[0.008]	[0.008]
ΔEPS_{t-1}	0.004	0.002	0.004*	0.006	0.002	0.002
	[0.004]	[0.004]	[0.002]	[0.004]	[0.004]	[0.002]
N	288	288	288	288	288	288
	MFP			HLP		
Eq (1c)	EPSI	EPSMKT	EPSNMKT	EPSI	EPSMKT	EPSNMKT
$\Delta prod_{t-1}$	−0.551**	−0.296	−0.496*	−0.763**	−0.964**	0.047
	[0.259]	[0.350]	[0.287]	[0.267]	[0.491]	[0.216]
$\Delta knoict_{t-1}$	1.090***	0.892***	1.150***	0.988***	0.989***	0.487***
	[0.141]	[0.132]	[0.147]	[0.133]	[0.137]	[0.144]
$\Delta kict_{t-1}$	0.061**	0.034	0.070**	0.081**	0.040*	0.105**
	[0.024]	[0.025]	[0.029]	[0.029]	[0.021]	[0.049]
ΔEPS_{t-1}	0.004	0.003	0.005	0.005	0.004	0.005
	[0.009]	[0.007]	[0.006]	[0.009]	[0.007]	[0.004]
N	288	288	288	288	288	288
	MFP			HLP		
Eq (1d)	EPSI	EPSMKT	EPSNMKT	EPSI	EPSMKT	EPSNMKT
$\Delta prod_{t-1}$	−0.586	−7.180**	−3.344**	−2.512**	−2.856**	−9.020***
	[1.169]	[2.618]	[1.646]	[1.067]	[1.449]	[2.657]
$\Delta knoict_{t-1}$	2.887***	4.129**	1.994*	4.001***	3.915***	5.561**
	[0.764]	[1.943]	[1.045]	[0.933]	[1.082]	[2.198]
$\Delta kict_{t-1}$	0.173	0.446**	−0.086	0.148	−0.321	0.653**
	[0.137]	[0.224]	[0.224]	[0.161]	[0.292]	[0.240]
ΔEPS_{t-1}	−0.068	−0.028	−0.170**	−0.069	−0.007	−0.200**
	[0.061]	[0.071]	[0.068]	[0.060]	[0.067]	[0.069]
N	288	288	288	288	288	288

* significant at 10% level; **significant at 5% level; ***significant at 1% level. EPS = environmental protection stringency; averages; EPSMKT = market based EPS index; EPSNMKT = non-market based EPS index; kict = log-ICT capital per hour worked; knoict = log non-ICT capital per hour worked.

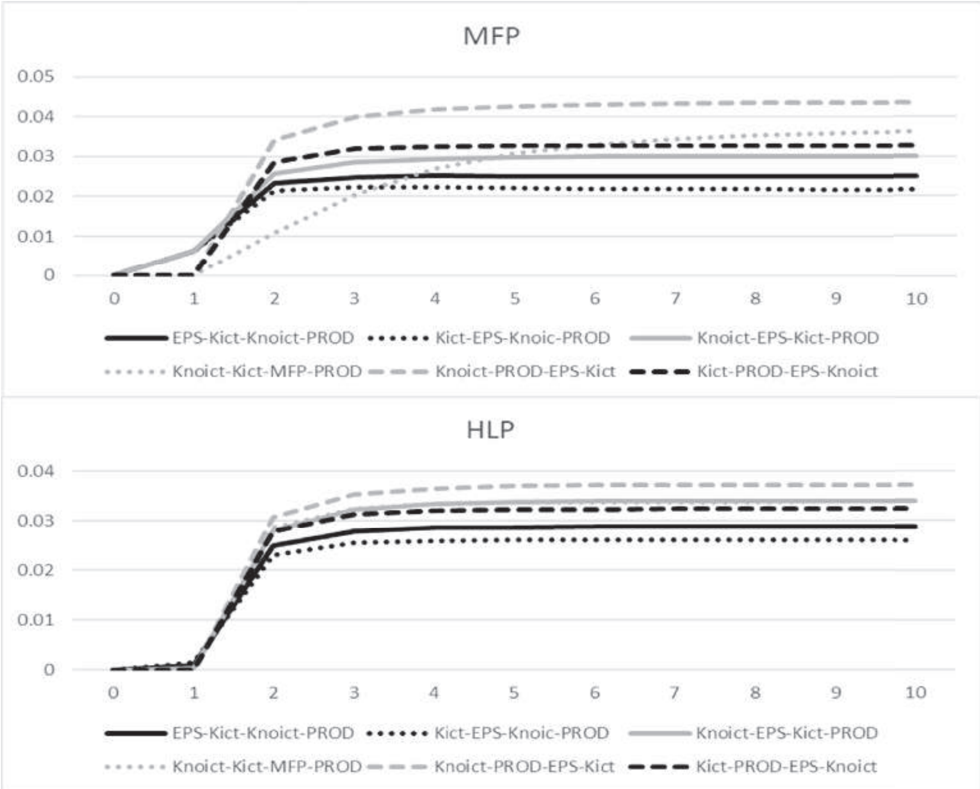

Fig. A2. Percentage of productivity forecast error variance due to a shock in EPS. Source: own elaboration.

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