Is green knowledge improving environmental productivity? Sectoral Evidence from Italian Regions

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This paper provides empirical investigation of the effects of environmental innovations (EIs) on environmental performances, as proxied by the environmental productivity (EP) measure. We focused on sectoral environmental productivity of Italian Regions by exploiting the Regional Accounting Matrix including Environmental Accounts (Regional NAMEA). Patent applications have been extracted by the Patstat Database and assigned to the environmental domain by adopting three international classifications of green technologies: the WIPO IPC green inventory, the European Patent Office climate change mitigation technologies classification (Y02) and the OECD ENV-Tech indicators. Econometric results outline that regions-sectors characterized by higher levels of green technologies (GTs) are actually those facing better environmental performance. These positive effects directly stem from the introduction of GT in the same sector, as well as from the introduction of GT in vertically related sectors.

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1 Introduction

The analysis of the relationship between environmental regulatory frameworks and environmental innovations (EIs) has gained momentum in the last decades, due to the increasing attention towards the reduction of pollutant emissions and the need to boost economic performances (Carrion-Flores and Innes, 2010; Carrion-Flores, Innes and Sam, 2013;The so called Porter hypothesis represents in this respect a basic reference, according to which the implementation of strict environmental regulation may have a twofold effect, i.e. triggering innovation efforts and stimulating productivity growth (Ambec et. al, 2013; Porter and van der Linde, 1995).

In this direction, most of the literature has focused on the importance of policy intervention as a determinant of EI (Acemoglu et al., 2012; Fischer and Newell, 2008; Nesta, Vona and Nicolli, 2014; Popp et al., 2009; Popp, 2002, 2006 and 2010;), grounded on the assumption that stimulating the generation and/or adoption of these technologies engenders positive effects on economic and environmental performance. This latter, however, has received only limited attention in empirical analyses. Carrion-Flores and Innes (2010) used sectoral environmental performances as a proxy for industry pollution targets to show that the relationship between green policy and innovation is bidirectional. More recent analyses have begun to explicitly estimate the determinants and the effects of environmental performances (Gilli et al., 2014; Costantini et al., 2013b; Cainelli et al., 2013; Ghisetti and Quatraro, 2013; Mazzanti and Zoboli, 2009).

This paper investigates the effects of EIs on pollutant emissions so as to provide a direct an explicit account of a link which is too often hypothesized rather than proven. In this sense, we aim at providing empirical grounds to the desirability of policies aiming at promoting EIs by wondering whether they actually improve environmental performance or not. We measure environmental performance through an indicator of environmental productivity (EP), as put forth by Repetto (1990), and exploit patent data in green technologies (GTs) as a proxy for EI. We thus investigate the impact of GTs on EP. In so doing, we first test for the existence of a direct effect of GTs on EP. Secondly, we test for the relevance of sectoral spillovers across vertically related sectors, as the generation of GTs is also likely to be stimulated by user-producer dynamics based on the derived demand of polluting agents for cleaner technologies. To test for this link, we implement a synthetic measure of vertical relatedness across sectors based on input-output tables. What we test is whether GTs generated by vertically related sectors affect EP as well.

The cross-sectoral analysis is carried out on a panel of Italian regions observed over the time span 2002-2005, and is based on the matching between regional National Accounting Matrix with Environmental Accounts (henceforth NAMEA) data, patent data and regional economic accounts. The Italian case has recently been the object of increasing attention, due to both the availability of emissions levels data at the regional and sectoral level, and to strong regional heterogeneities in environmental performances attention (e.g. Costantini et al., 2013, Ghisetti and Quatraro, 2013, Marin and Mazzanti, 2013; Mazzanti and Zoboli, 2009). The economic literature on sectoral emission patterns and "delinking" also supports the appropriateness of a sector-based analysis because of the relevant specific patterns emerged in previous literature (Marin and Mazzanti, 2013; Marin et al., 2012; Mazzanti and Zoboli, 2009; Mazzanti et al., 2008).

The econometric results identify robust patterns of relationship between EI and EP for different classes of emissions. GTs, both those within sector and those of vertically related sectors, exert a positive impact on EP. This would support the hypothesis that improvements in EP are driven by higher propensity to innovate in green technologies both within sectors and in vertically related sectors.

The rest of the paper is organized as follows. Section 2 articulates a framework relating EP, EI and GTs at the sectoral and regional level and constructs the working hypotheses. Section 3 outlines the empirical context of the analysis, while Section 4 presents data, methodology and variables. In section 5 we show the results of the econometric analyses, and the main robustness checks we implemented. We provide the conclusions and articulate a discussion into Section 6.

2 Regional EP and green technologies

A quite large body of empirical literature has investigated the relationships between innovation and productivity at different levels of analysis, moving from the seminal Zvi Griliches' (1979) contribution. Most of the analyses have been carried out at the firm or country level, with special focuses on sectoral comparisons. Regional analyses of the relationship between innovation and productivity have instead appeared only recently (Quatraro, 2009 and 2010; Dettori et al., 2012;

Paci and Marrocu, 2013). These works point to the positive effects of innovation on regional productivity growth, even after controlling for region-specific factors and the impact of neighbor regions' performances.

While usually analyses of innovation and productivity use the traditional measure of total factor productivity (TFP) as a dependent variable, the literature in the field of environmental economics has recently begun to consider a peculiar productivity index, i.e. the environmental productivity (EP), which was originally proposed by Repetto (1990) (Jaffe et al., 1995; Yaisawarng and Klein, 1994; Huppes and Ishikawa, 2005)[3]. In this perspective, value added is rescaled by non-marketed inputs and outputs (e.g. air emissions or natural resources). EP represents therefore a measure of environmental performance allowing to appreciating changes in pollutant emissions at different levels of the analysis (Huppes and Ishikawa, 2005).

Previous empirical studies have focused on the analysis of the determinants of environmental performances, usually measured by the ratio between air emissions and value added, which is nothing but the inverted measure of environmental productivity. Due to the difficulty to obtain firm-level data on emissions, these previous contributions have been mostly carried out at the national, sectoral or regional levels and exploited data from environmental hybrid economic-environmental accounting matrixes. When the empirical setting is firm-level, the lack of data on firms' (or plants') emissions have been often overcome by exploiting sectoral data to construct sectoral emission intensity as exogenous variables.

Firm-level analyses have shown for example the existence of a non-linear relationship between environmental and economic performances, both in the Italian and the Mexican contexts (Cainelli et al., 2013; Sanchez-Vargas et al., 2013). Costantini et al. (2013), carried out a regional and sectoral analysis to test whether environmental performances are affected by both internal innovations (measured by environmental patents) and technological and environmental spillovers from neighbor regions in the Italian context. Ghisetti and Quatraro (2013) focused on the Italian case as well, and found that regional and sectoral environmental performances are likely to trigger EI, as measured by patents in green technologies, also in vertically related sectors. Gilli et al. (2014) adopted instead a measure of environmental productivity (EP) and investigate the role

[3] Following Kortelainen (2008) it is worth stressing that some authors have defined environmental productivity as a ratio of the environmental sensitive total factor productivity (TFP) index to the traditional total factor productivity index (see e.g. Ball et al., 2004, Managi et al., 2005 and Managi, 2006), which clearly is a different measure.

of complementarities of different typologies of innovation in shaping EP at the EU level, by using regionalized data from the Community Innovation Survey (CIS).

The analysis of the effects and determinants of EP emerge as a complement to the analysis of the relationship between differential regulatory frameworks and EI (Brunnermeier and Cohen, 2003; Del Rio, 2009; Popp, 2002, 2006, 2010; Porter and van der Linde, 1995). The main rationale behind government intervention to stimulate the generation and/or the adoption of these technologies lies indeed in their expected positive effects on emissions abatement, which should overall improve industrial activities' sustainability. In this perspective, our analysis of the impact of EI on EP aims at providing empirical foundations to those policy instruments aimed at supporting the generation and/or adoption of EIs.

The *derived demand* of GTs is also likely to play a key role in this context: the interplay between EPs patterns and the (derived) demand pull dynamics (Schmookler, 1957) allows for appreciating the relevance of vertical linkages amongst upstream firms producing EIs and downstream firms employing these technologies in their production processes (Cainelli and Mazzanti, 2013; Ghisetti and Quatraro, 2013). Downstream firms resort indeed to upstream firms for the supply of new and more environment-friendly technologies to be introduced in the production process. The interactions between users and producers matter in shaping the ultimate effects of GTs, in such a way that the generation and the adoption of new technologies become strictly complementary (von Hipple, 1988; Lundvall, 1992; Nelson, 1993).

In view of the arguments articulated so far, we are now able to spell out our working hypotheses. EI, which we hereby approximate by patents in green technologies (GTs), are expected to drive EP and improve environmental performance.. Secondly, the interplay between GTs and derived demand-pull mechanisms brings vertical linkages to the center of our analysis, where the improvement of EP is expected to be triggered by the derived demand of polluting firms for environmental technologies. Since the analysis is conducted at the sectoral and regional level, we can hypothesize that both direct and vertically moderated effects of GTs generation yield a positive effect on EP.

3 Empirical strategy

3.1 Data and variables

The main hypothesis of this study is that EIs exert a positive effect on EP, both within sector and across vertically related sectors. The EP measure has been built at the regional-sectoral level using the Regional NAMEA collected by the Italian Statistical Office (ISTAT) for the year 2005. Italy is the only country providing the regional breakdown for such data. NAMEA is a powerful data instrument: a hybrid environmental-economic accounting matrix that allows a coherent assignment of environmental pressure to economic branches (ISTAT, 2009; Tudini and Vetrella, 2012).[4]

NAMEA data at the national level have been exploited in several studies (e.g. Marin et al., 2012, Marin and Mazzanti, 2013, Mazzanti et al. 2008, Mazzanti and Montini 2010b, Mazzanti and Zoboli 2009), while the regional extension (at the NUTS 2 level) of this dataset to the best of our knowledge has been exploited only in a few cases[5](e.g. Costantini et al., 2013b, Ghisetti and Quatraro, 2013, Mazzanti and Montini, 2010).

EP have been built by scaling the value added by selected air emissions and then log-transformed, as reported in Equation (1). In other terms, it is an indicator value added per unit emissions.

$$EP_{ij} = \log\left(\frac{VA_{ij2005}}{EMISSIONS_{ij2005}}\right) \qquad (1)$$

The higher the emissions relative to the value added, the lower the value in the indicator and the worse is the EP of that region-sector. Contrarily, low levels in emissions with respect to value added make the overall indicator have higher values. We chose to focus on the aggregated emissions by environmental impact, Greenhouse Gases (GHG), Acidifying Gases (AC), and Carbon dioxide (CO2) [6].Consequently we will separately estimate our empirical model for each

[4]Data on air emissions are available for the following pollutants: carbon dioxide (CO2), nitrous oxide (N2O), methane (CH4), nitrogen oxides (NOX), sulphur oxides (SOX), ammonia (NH3), non-methane volatile organic compounds (NMVOC), carbon monoxide (CO) and lead (Pb). Data on aggregated emissions are available for greenhouse gases (GHG), Acidifying gases (AC) and Ozone precursor emissions (OZ).

[5] Regional NAMEA is a powerful dataset as it allows to attribute emissions not only to sectors but also to the Regions responsible for their generation, following a methodology that directly links local resident's units economic activities to the emissions stemming from them (EC, 2009). The regional level of investigation is consequently very appropriate, as national data are constructed by aggregation of local ones and not vice versa.

[6] As aggregate emissions are built by grouping and weighting the equivalent tones of the previous pollutants, we decided to focus on GHG, AC, which are aggregate indicators to avoid overlaps and on CO2. CO2 is the main

of the different chosen emissions classes. We will therefore employ four dependent variables: EP_CO2, EP_AC and EP_GHG . The evidence about the regional and sectoral distribution of EP is reported in Tables 1 and 2.

>>> INSERT TABLES 1 AND 2 ABOUT HERE <<<

As data were only available for 2005, to mitigate reverse causality issues we modelled all our explanatory variables in the previous period, i.e. from 2002 to 2004.

EIs are approximated by our key explanatory variable, *GT*, which reflects the number of patent applications in green technologies by Italian firms and is disaggregated at the regional and sectoral level[7]. To construct GT a multistep methodology has been followed.

First, patent applications have been drawn from the PATSTAT database. It is well known that PATSTAT does not provide standardized information on regional location and sector classification of applicants. To assign patents to Italian NUTS 2 regions we use the OECD Reg Pat Database (OECD, 2013). The matching between patent applications and the NACE sector classification has been carried out as it follows. We first assigned patent applications to Italian firms on the basis of the relational table used in Marin (2013), and described in detail in Lotti and Marin (2013)[8]. This allows to establishing a link between patent applications and the Bureau Van

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component of GHG, for this reason we expect similar results for CO2 and GHG but we are still willing to see whether different dynamics are at stake. For this reason we consider environmental productivities for CO2 as well.

[7] It is necessary to acknowledge that measuring innovations (and environmental innovation as well) through patent applications data presents some drawbacks that require to be mentioned. On the one side, not all patent applications become innovations, for instance in the presence of strategic patenting. On the other side one of the widely accepted definitions of EI stresses that EI is "the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives" (Kemp and Pearson, 2007:7). The measurement of EI through patent data cannot perfectly fit this definition as it would not allow to account for innovations that are only new to the firm adopting them and it excludes not technological innovations such as organizational ones that should be accounted as EI. Furthermore patents suffer of sector-specificity, they are not the only available tool for firm to protect its inventions and the propensity to patent vary over time and depends on firms's size (Griliches, 1990, 1998; Pavitt, 1985). However patents are proved to be very reliable proxies for knowledge and innovation (Acs et al., 2002; Hall et al., 1986). An alternative would be to measure EI through the exploitation of innovation survey data containing questions on EI, such as the Community Innovation Survey (CIS) 2006-2008 for firms or the Flash Eurobarometer surveys (315, 342 or 381) for entrepreneurs. However, in both cases it is not possible to obtain information on the Regions of the Italian respondents that allow to match data on regional emissions (available only for Italy) with data on regional environmental innovativeness, but, as we discussed, we believe that the regional level of investigation is the most appropriate one. Furthermore, the alternative of using innovation survey data has the drawback of being subjective, as data are self-reported by the respondent, rather than being objectively collected as in the case of patents.

[8]This matching method starts from the harmonization routines proposed by NBER Patent Data Project (https://sites.google.com/site/patentdataproject/) to standardize and clean the names both in AIDA and PATSTAT,

Dijk identification code. Then we searched these firms in the Bureau van Dijk Orbis database (July 2012 release) in order to extract information on the sectoral classification. We finally used the information about the NUTS 2 region and sectoral classification in order to aggregate out the number of patent applications at the region and sectoral level.

Secondly, we used the technological classes of patent applications to discriminate between patents in environmental (related) technologies, from now on Green Technologies (GTs) and patents in technology fields which are not related to environmental improvements. Several international classifications have been developed to make this discrimination feasible. Each classification has its own limits in terms of missing technologies, as discussed in Costantini et al. (2013a). In order to check for the robustness of our results and to mitigate potential biases, we chose to run different estimations by separately adopting the three existing classifications. Two of these classifications, i.e. the World Intellectual Property Organization(WIPO) IPC Green Inventory (WIPO, 2012), and the OECD EnvTech (OECD, 2011), are based on the technological classes as defined by the International Patent Classification (IPC). The remaining classification is the result of clinical analyses of patent applications which ended up in the European Classification System (ECLA). Within ECLA, environmental technologies are identified by the Y02 class. In so doing, we make sure that our results do not depend on the chosen classification[9].

The WIPO IPC is a well-established classification and allows to assign patents to the following areas: (a) alternative energy production, (b) transportation, (c) energy conservation, (d) waste management, (e) agriculture/forestry, (f) Administrative, regulatory or design aspect and (g) nuclear power generation. The OECD Indicator of Environmental Technologies EnvTech identifies seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting. Lastly, the ECLA classificationis grounded on the environmental aim of each patent. So far, this classification

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then it proposes a set of cleaning procedures required by the specificities of Italian data and ends with following the Thoma et al (2010) harmonized list of names and locations for AMADEUS and PATSTAT.

[9]In our sample OECD is the most extensive classification, it is followed by the WIPO IPC Green Inventory, green patents and, lastly comes ECLA Y02. It has to be noted that ECLA Y02 is still incomplete, as it emerges from its documentation (http://worldwide.espacenet.com/classification?locale=en_EP#!/CPC=Y02). Details on the regional and sectoral heterogeneities of GT by the three classifications are provided in Table 3 and Table 4.

allows to tagging technologies for adaptation or mitigation to climate change (Y02), in terms of buildings (Y02B), energy (Y02E), transportation (Y02T) and capture, storage sequestration or disposal of GHG (Y02C).

The count of GT between 2002 and 2004 has been weighted by the mean full-time equivalent job units in 2002-2004 of region and sector and then log-transformed, as described in Equation (2).

$$GT_{ij} = \log\left(\frac{GT_{ij2002-2004}}{FTE_{ij2002-2004}}\right) \qquad (2)$$

Sectoral and Regional distributions of environmental technologies by different classifications have been reported, respectively, in Tables 3 and 4.

>>> INSERT TABLES 3 AND 4 ABOUT HERE <<<

We also account for GT generated by strongly interrelated sectors (W*GT), weighting GT generated by the remaining sectors according to their sectoral relatedness. To do that we built a weighting matrix W exploiting Input-Output Supply and Use tables which gives higher values to the emissions generated by strongly related sectors.).We used, as anticipated, the Italian Input Output "Supply" and "Use", which contain the flows and value of commodities produced by each industry and the flows and value of commodities consumed by each industry respectively, and constructed a matrix for the input-output relatedness between industriesTo build W we drew upon the methodology proposed by Essletzbichler, (2013) and used the Italian Input Output "Supply" and "Use", containing flows and value of commodities produced and consumed by each industry[10].

W*GT follows the formula in Equation (3):

$$W_{j,l\neq j}GT_{i,l\neq j} = \log\left(\frac{\sum_{l\neq j} W_{j,l\neq j} {}^{*}GT_{i,l\neq j,2002\text{-}2004}}{FTE_{ij2002\text{-}2004}}\right) \qquad (3)$$

We then controlled for the role played by real value added (VA) by labour productivity (LP) and the ratio of exporting activities in Europe on real value added (EXPORT)[11].

[10] The methodology we followed builds W from the following formula, in which Fj,l and Fl,j represents flows between industry i and j, and have been built by multiplying the matrix of the share of one unit of the commodity c produced by industry l by the value of c consumed by industry j and vice versa: $W_{j,l} = \frac{1}{2}\left(\frac{F_{j,l}}{\sum_{j=1}^{n} F_{j,l}} + \frac{F_{l,j}}{\sum_{l=1}^{m} F_{l,j}}\right)$

[11] Whereas for VA and LP we exploited the of region-sector average value between 2002 and 2004, the value for EXPORT_UE is only available at the regional level.

EP might also be depending on the presence of an environmental policy. Without any direct policy measure we adopted a proxy for environmental policy (POL) that we built as the natural logarithm of the ratio between average expenditure for environmental protection (only capital expenditure) (as in Costantini and Crespi, 2008) in 2004 and the mean value added of the same year[12].

Denser Regions are expected to face differences in environmental productivities than other regions. To control for this we constructed DENSITY as the density the ratio of mean population in each Region on its area in 2002-2004. Some locational variables have been included to capture geographical heterogeneities $\sum \rho_i$ through a set of dichotomous variable: northwest (NORTHW), northeast (NORTHE), center (CENTRE) and south (SOUTH – taken as benchmark).

Our sample includes manufacturing, electricity, water and gas supply sectors and consists of 10 NACE Rev 1.1 sectors in 20 Region, which amounts to a pool of 200 potential observations, which falls to 199 because of missing values. To capture for the most polluting sectors we built a dummy variable DIRTY which is equal to one in the presence of a strongly polluting sectors[13].

As energy consumption strongly impacts on emissions, regional energy consumption at sectoral level has been accounted for through the deployment of TERNA data[14]. The variable ENERGY represents the natural logarithm of the ratio between mean energy consumption and the mean value added in 2004.

Furthermore it is expected that Regions in which a metropolitan area exists are subject to different EP. Consequently a dummy variable equal to one in the presence of metropolitan areas (METRO) has been constructed[15].

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[12] As the first available year in the dataset of environmental protection expenditures for Italian Regions is 2004, POL is constructed as ratio of environmental protection expenditure on regional value added in 2004. This variable is only Region variant and not sector variant.

[13] Those are DF, DG, DI and E [Nace Revision 1.1]: Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of chemicals, chemical products and man-made fibers; manufacture of other non-metallic mineral products and Energy, water and gas supply.

[14]TERNA S.p.A. publishes "Statistical Data on electricity in Italy" covering the principal aspects of the national electricity sector, among which energy consumption by sector and region. Data are available at the region-sector level from 2003. We thus constructed ENERGY as the ratio of region-sector energy consumption in 2004 on the value added in the same year.

[15] The following metropolitan areas are considered: Neaples, Milan, Rome and Turin.

A summary description of the variables included in our empirical analysis, along with their relevant descriptive statistics, is available in Table 5.

>>> INSERT TABLE 5 ABOUT HERE <<<

We ground our empirical analysis on manufacturing and electricity, water and gas supply sectors (respectively ATECO D and E[16]).The manufacturing sector is at the center of our analysis as it is at the same time having strong environmental impact and high potential for innovation (Marin and Mazzanti, 2013). Electricity, water and gas supply sector has been also included in our analysis because, in absolute levels, is one of the sectors mostly responsible for emissions in all the categories we consider (Regional NAMEA: ISTAT).

3.2 Methodology

As only observations for sector-region emissions in the year 2005 are available, the analysis we are implementing will be a cross-sectional one, with the dependent variable at t and all the explanatory variables observed in previous years t-1, i.e. from 2002 and 2004[17].

EP has been built with respect to different air emissions, i.e. AC, CO2 and GHG. Accordingly, we estimated the following equation separately for each and every emission considered to build the environmental productivity variable (EP).

Moreover GT and W*GT are themselves strongly correlated, as it emerges from the Spearman correlation matrix in Table 6. For the same reason outlined above their joint inclusion in a single estimation is not possible.

The following baseline model is estimated:

$$\begin{aligned}(\mathrm{EP}_{ijt})=&\beta_0+\beta_1(\mathrm{GT}_{ijt-1})+\beta_2(\mathrm{LP}_{ijt-1})+\beta_3(\mathrm{POL}_{i\,t-1})+\beta_4(\mathrm{VA}_{ijt-1})\\&+\beta_5(\mathrm{DENSITY}_{it-1})+\beta_6(\mathrm{EXPORT\_UE}_{i\,t-1})+\beta_7(\mathrm{DIRTY}_j)+\sum\rho_i+\varepsilon_{ij}\end{aligned} \quad (4)$$

GT will be then substituted by W*GT.

$$\begin{aligned}(\mathrm{EP}_{ijt})=&\beta_0+\beta_1(W*\mathrm{GT}_{ijt-1})+\beta_2(\mathrm{LP}_{ijt-1})+\beta_3(\mathrm{POL}_{i\,t-1})+\beta_4(\mathrm{VA}_{ijt-1})\\&+\beta_5(\mathrm{DENSITY}_{it-1})+\beta_6(\mathrm{EXPORT\_UE}_{i\,t-1})+\beta_7(\mathrm{DIRTY}_j)+\sum\rho_i+\varepsilon_{ij}\end{aligned} \quad (5)$$

[16]Results are robust to the exclusion of the Energy, water and gas supply sector. Furthermore results are robust to the inclusion of the construction sector. Table are available upon request.
[17]With the exception of POL and ENERGY for which t-1 corresponds to the year 2004.

Where i= 1,…, 20 indicates the Region j=1, … , 10 stands for the Sector and β_0 to β_8 the coefficients to be estimated. The error term is decomposed so as to account for region (ρ_i), fixed effects. The region (ρ_i), fixed effect is accounted for with the inclusion of 4 locational dichotomous variables: *NORTHEAST*, *NORTHWEST*, *SOUTH* and *CENTER* (benchmark).

Estimations of the models (4) and (5) are carried out in three separate steps. In a first step GT and W*GT follow the WIPO IPC Green Inventory to tag environmental technologies. In a second one the classification exploited is the OECD EnvTech one. Lastly, the EPO ECLA is used.

In a second step we control for energy consumption ENERGY, given the expected environmental impact of energy consumption in terms of CO2 and GHG emissions, and for the presence of metropolitan areas in the region METRO, estimating equations (6) and (7).

$$\begin{aligned}(EP_{ijt}) =& \beta_0+\beta_1(GT_{ijt-1})+\beta_2(LP_{ijt-1})+\beta_3(ENERGY_{ijt-1})+\beta_4(POL_{i\,t-1})+\beta_5(VA_{ijt-1}) \\ &+\beta_6(DENSITY_{it-1})+\beta_7(EXPORT\_UE_{i\,t-1})+\beta_8(DIRTY_j)+\beta_9(METRO_i)+\sum \rho_i+\varepsilon_{ij}\end{aligned} \tag{6}$$

$$\begin{aligned}(EP_{ijt}) =& \beta_0+\beta_1(W*GT_{ijt-1})+\beta_2(LP_{ijt-1})+\beta_3(ENERGY_{ijt-1})+\beta_4(POL_{i\,t-1})+\beta_5(VA_{ijt-1}) \\ &+\beta_6(DENSITY_{it-1})+\beta_7(EXPORT\_UE_{i\,t-1})+\beta_8(DIRTY_j)+\beta_9(METRO_i)+\sum \rho_i+\varepsilon_{ij}\end{aligned} \tag{7}$$

We estimate Equation (4) to (7) through an OLS estimator with Huber-White corrected standard errors.

4 Results and Discussion

This paper aims at investigating the effects of EI on EP, by focusing on sectoral evidence for Italian regions. It is worth recalling that according to our main hypotheses EIs are expected to engender significant improvements of EP. Moreover, the interplay with derived-demand dynamics also suggest that improvements in EP are driven by EIs generated in vertically related sectors.

As stated in the previous section, we have tested two hypotheses using different operational specification of EI, which are based on patents’ technological classes. Table 7 reports the results obtained by employing the well-established WIPO IPC Green Inventory to assign patents to the green realm. The model tested refers to the baseline specification (Equations (4) and (5)) .

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The first column shows the estimation of the effects of EI on EP measured in terms of CO_2 emissions. The coefficient of interest is the one of GT, and it is positive and significant, in line with our expectations. An increase of EI engenders an increase of EP, i.e. either an increase of value added or a decrease of emissions or both. Column (2) shows the results for EP measured in terms of GHG. Also in this case GT shows a positive and significant coefficient. while the one of the DIRTY dummy is negative and significant. Column (3) reports the results obtained when EP is built in terms of acidifying gases. In this case the coefficient of GT, although positive, is not significant. Overall the positive effect of GTs appears to be significant only when Greenhouse gases at general and CO_2 in particular, are considered.

Columns (4) to (6) show the results concerning the effects of GT generated in vertically related sectors. The former reports the evidence about carbon dioxide, in which W*GT has a positive and significant coefficient. Column (5) provides the estimates concerning the effects of W*GT on EP calculated with respect to GHG. Also in this case the coefficient is positive and significant. Finally, column (6) focuses on acidifying gases, and it shows that W*GT does not significantly affect EP.

The overall econometric evidence using the WIPO Green Inventory suggests that the impact of GT, both direct and moderated by vertical linkages, on EP is positive. Such relationship however holds only for GHG and carbon dioxide in particular.

In order to check whether the results are sensitive to different classification schemes for GT, Table 8 shows the results obtained by using the OECD Env Tech. EP measured with respect to carbon dioxide is positively affected by GT, as showed in column (1). The same applies to more general GHG category (column (2)). Even in this case, EP calculated on acidifying gases seem not to be affected by the generation of GTs, as showed in column (3).

>>> INSERT TABLE 8 ABOUT HERE <<<

As for the previous table, columns (4) to (6) reports the results concerning the effect of GT generated in vertically related sectors on EP. The W*GT variable exhibits a positive and significant coefficient, suggesting that EP calculated on CO_2 is likely to increase when GT from vertically related sectors increase as well (column (4)). When GHG in general are at stake, the effects of W*GT is still positive and significant (column (5)), while the EP measured by looking at acidifying gases WGT does not yield any significant effect. The evidence obtained by using the OECD EnvTech classification is fairly consistent with that obtained by using the WIPO method.

A final sensitivity check is carried out in Table 9, wherein we use ECLA Y02 tag for green innovations. In column (1) it is shown that EP based on carbon dioxide is positively and significantly affected by GT. Similar evidence is found also in column (2), wherein EP is calculated by using GHG. Differently from previous estimations, also the EP calculated on acidifying gases is significantly affected by GT.

>>> INSERT TABLE 9 ABOUT HERE <<<

The results concerning the effects of W*GT are consistent with previous estimations, and show that significant and positive coefficients can be found when EP builds upon CO_2 and GHG, while no significant effects are found when using acidifying gases.

In sum, the main finding is that GT generated in the region-sector positively affects EP of the region-sector. Keeping in mind that EP has been built as the ratio of value added on air emissions, the interpretation is indeed that higher is the value of this indicator the better is the environmental performance of that region-sector, as it implies lower emissions associated to the value added generated. This result holds for both CO_2 and the more general GHG category. A similar result is found for acidifying gases only when we use the ECLA classification.

When we look at GT generated by sectors to which a strong vertical relatedness exist (W*GT) we find a positive and significant correlation with EP. We can confirm our second hypothesis according to which EI's effects on EP pass also through the user-producer dynamics.

EP constructed with respect to CO2 and to GHG show therefore very similar dynamics, confirming our expectations, which are grounded on the fact that CO2 is the main component of GHG.

Moreover, when adopting the EPO ECLA classification to assign GT a slightly significant and positive effect on GT and W*GT also on EP for Acidyfing gases emerge. This suggests that our hypotheses are still confirmed but also that results are slightly sensible to the choice of the classification adopted.

Moving to the discussion of the remaining explanatory variables, we find that results give support to our expectations. Labour productivity (LP) positively affect environmental productivity, as better LP improves value added, i.e. the numerator of our EP indicator in the case of AC gases, but this result does not hold when EP variable has been constructed with respect to CO2 and GHG emissions. The DENSITY of a Region is slightly found to be a relevant determinant of EP and this correlation has a positive sign: the denser is a Region the better is the EP expected. DIRTY sectors show significantly worse environmental dynamics than the other sectors (DIRTY is negative and significant). Locational variables do play a role in explaining EP. In particular belonging to a central and, in some cases, to a northern-western Region positively impacts EP with respect to southern Italian Regions (i.e. the benchmark).

Environmental Policy (POL) and exporting activities (EXPORT) are on the contrary not significantly affecting EP.

4.1 Robustness check

Results presented in the previous section provide support to our hypotheses according to which EIs contribute to the improvement of environmental performance, and vertical relationships play a key role due to user-producer relationship. In order to carry out further robustness checks, we show in Table 10 the results of estimations run on Eq. (6) and (7).

>>> INSERT TABLE 10 ABOUT HERE <<<

In these estimates we also account for the potential effects of energy consumption (ENERGY) and of the presence of large metropolitan areas (METRO) on pollutant emissions, above all CO_2 and GHG. The results suggest that these two variables do not yield any significant effects on EP, no matter which classification is used to tag patents as green.

However, it must be noted that the evidence concerning the effects of GT and W*GT appears to be robust and even stronger when these additional control variables are included in the model. Indeed, besides the fairly persistent effect on CO_2 and GHG, across the three classification methods (columns (1a), (2a), (1b), (2b), (1c) and (2c)), we find evidence of significant effects of GT on acidifying gases, when both the WIPO Inventory method and the ECLA classification are used (columns (3a) and (3c)), while W*GT is significant only as far as the ECLA classification is concerned (column (6c)).

A further issue concerns the sensitivity of the estimates including W*GT to the specification of the weighting matrix W. We decided therefore to carry out separate regressions by using a binary weighting matrix in which the value of each cell is equal to 1 if the observed weight is higher than the value at the 75th percentile, 0 otherwise. The results of these estimations are reported in Table 11, which clearly concern only the equations including W*GT, Eq(7).

>>> INSERT TABLE 11 ABOUT HERE <<<

The evidence is consistent with that showed in the previous tables. W*GT is indeed featured by significant and positive coefficients as far as its effects on carbon dioxide and GHG are concerned across all the three different GT classification schemes. A positive and significant effect on acidifying gases is instead found only when the ECLA Y02 classification is adopted.

4.2 Endogeneity issues

The evidences discussed so far provides a clear-cut picture of the effects of EI on EP. However, it is fair to note that some endogeneity issues may arise in this context, as put forth by Carrion-Flores and Innes (2010) and Carrion-Flores, Innes and Sam (2014). Environmental policies, following the Porter hypothesis, may induce the generation and diffusion of innovation and this may engender competitive gains. These innovations are likely to actually improve environmental performances. Such an improvement may in turn push policymakers to make emission targets even more stringent, stimulating further efforts to introduce EIs.

Although the role of environmental policies in the context under scrutiny, i.e. Italian regions, is not expected to be so strong (Ghisetti and Quatraro, 2013) given the weakness of the stringency of Italian policy (Haščič et al, 2009), we nonetheless provide in this section a robustness test to reduce potential endogeneity problems.

In order to cope with possible endogeneity of the GT and W*GT regressors we have run instrumental variable (IV) regressions. Although our estimates are carried out on cross-sectional data (due to the lack of time series for the dependent variable), we are able to obtain explanatory variables, and in particular GT on different time periods. We therefore calculated GT and W*GT variables for the period 1999-2001 and used these lagged variables to instrument the 2002-2004 values which were used in the previous regressions[18]. The results of of IV estimations are reported in Table 12.

>>> INSERT TABLE 12 ABOUT HERE <<<

For the sake of brevity we only report the estimations including GT and W*GT calculated by using the WIPO Inventory Method. The estimations employing the ECLA and OECD classifications yield very similar results. Results are coherent with previously discussed evidences: GT shows a positive and significant effect on EP built from CO_2 and GHG, while no significant effects can be found on acidifying gases. The same applies to the effects of W*GT.

At the bottom of each column we report the results of the Hausman endogeneity test (Hayashi, 2000)[19]. The results of the test suggest that endogeneity is not an issue in our estimations, as the p-value of the Hausman test is high enough to lead us not to reject the null hypothesis of exogeneity of the regressor. Such evidence is consistent with our expectations, based on the evidences that previous literature outlined on the weakness of the Italian environmental policy, which is mainly driven by its weak stringency and flexibility (Haščič et al, 2009) and by its low stability and transparency (Johnstone et al., 2010; 2012),

5 Conclusions

Environmental innovations are seen as tools leading to a win win situation, as they are able to restore competitiveness and to improve sustainability (EC, 2010). Whereas previous literature focused on the competitiveness and profitability effects of EI (see e.g. Ambec and Lanoie, 2008; Ghisetti and Rennings, 2014), this paper tests their environmental effects. It evaluates whether the generation of GTs lead to an improvement in environmental productivity in Italian regions-sectors. Our results provide support to the hypothesis that innovations in the green domain do actually improve environmental performance. Furthermore, the influence of GTs on EP is not only direct but also moderated by the derived demand for GTs. These findings lead to relevant policy implications. The most straightforward of which is that policies designed at

[18] An alternative candidate as an instrument would have been the data on environmental R&D expenditure. However it is not possible to find reliable regional and sectoral breakdown.

[19] This test is calculated as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. Unlike the Durbin-Wu-Hausman tests, this statistic that is robust to violations of conditional homoscedasticity.

favoring the adoption and/or generation of EI as well as at reducing the barriers are sensible in that through EI they make regional and sectoral EP improve.

The demand pull hypothesis has a new scope of application in this direction. It does not apply any longer to any undifferentiated increase of demand, as in the Kaldorian tradition. Nor is it limited to the demand for capital goods, as in the tradition that elaborates upon Schmookler's analysis. The results of our analysis allow to qualifying the traditional Keynesian argument supporting the role of government expenditure as a contribution to the aggregate demand, by providing the rationale for demand driven innovation policies aiming at promoting the development of industrial activities involved in the production of green technologies.

The scope for further extensions of this work is also wide. As pollutants are in the air they can easily move across geographical boundaries and affect the environment of closer regions. It would therefore be interesting to investigate the impact of geographical proximity on the EP in neighbor regions by exploiting spatial econometric techniques. However, we have to recall that NAMEA data are actually measuring the regional *emissions* of selected pollutants, and not the level of pollutants recorded in each region. The implication is that on the one hand it is true that a region's emissions might flow to the neighbors, but on the other hand available data for each region measure only its own emission, and not the overall level of air pollutants recorded in "its" air. Consequently it is not reasonable to assume that emissions in one region affect the emissions of its neighbors, as what they actually influence is the environment 'at large', i.e. something for which we have no appropriate data. Another relevant issue concerns the influence of the competences locally accumulated in the course of time on the establishment of industrial activities aiming at producing EIs. Empirical analyses should assess the extent to which the incentives to the local creation of new technology based activities such as 'green technologies', should be grounded on the accurate analysis of both the comparative advantages developed over time in a specific area and of the relative position of such technologies in the technological landscape. Stimulating local agents to jump to new activities far away from their cumulated competencies could be indeed inefficient and unsuccessful (Colombelli, Krafft, Quatraro, 2014).

A clear limitation of the current work lies in the cross-sectional nature of the analysis. We made our best to overcome reverse causality issues by lagging the explanatory variables in t-1 and by accounting for regional and sectoral variables to capture individual characteristics. However the exploitation of a panel data for regional air emission would have allowed to completely overcoming this issue. Unfortunately such a dataset at the regional level is not available yet, so such an analysis is not feasible. At the same time, the choice of a Region-Sector focus is one of the main elements of originality of the current work, and thus we believe that the choice of this dataset, although cross-section, remains an accurate and appropriate choice to test for our research hypothesis, given the increasing relevance of meso levels of analysis (Pavitt, 1984, Malerba 2004).

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Table 1 - Sectoral Distribution of EP

Nace Rev1.1	GHG	AC	CO2
A	0.76	1.78	3.56
B	1.11	3.79	1.11
C	2.83	31.27	3.19
DA	2.45	56.48	2.69
DB	4.37	77.12	4.51
DC	4.62	102.90	5.32
DD, DH, DN	4.73	88.59	4.84
DE	3.11	107.26	3.17
DF, DG	0.89	22.34	0.95
DI	0.35	3.68	0.36
DJ	6.56	77.94	6.78
DK, DL, DM	7.27	149.25	7.43
E	1.23	37.63	3.21
F	14.40	134.12	14.94
G	6.43	64.22	6.62
H	13.16	149.81	13.62
I	2.14	14.33	2.20
J	46.21	492.19	47.41
K	28.61	279.01	29.43
L	23.24	168.67	24.27
M	55.17	853.05	56.13
N	24.75	451.96	37.26
O	1.13	29.23	6.43
P			

Note: (real VA on emission, before log transformation)

Table 2- Regional distribution of EP

nuts2	GHG	AC	CO2
ITC1	10.93	166.07	12.03
ITC2	6.09	90.16	6.85
ITC3	12.97	195.46	15.14
ITC4	12.13	186.75	12.97
ITF1	9.85	136.78	11.06
ITF2	10.04	109.94	11.00
ITF3	12.95	164.70	15.08
ITF4	9.95	129.04	11.08
ITF5	8.92	116.24	10.15
ITF6	11.89	122.11	13.72
ITG1	13.58	154.31	16.00
ITG2	12.43	137.62	13.92
ITH1, ITH2	9.83	131.73	11.60
ITH3	11.29	154.97	12.26
ITH4	11.73	153.95	13.25
ITH5	9.97	144.92	10.54
ITI1	11.73	185.45	12.75
ITI2	10.53	138.48	11.46
ITI3	12.66	167.40	13.93
ITI4	14.95	202.57	15.94

Note: (real VA on emission, before log transformation)

Table 3 - Sectoral distribution of environmental technologies in 2002-2004

	WIPO IPC	%	OECD EnvTech	%	EPO ECLAY02	%
A	11	0.2%	0	0.0%	12	0.3%
B	18	0.4%	30	0.3%	41	0.9%
C	171	3.7%	58	0.6%	27	0.6%
DA	7	0.2%	9	0.1%	48	1.1%
DB	21	0.5%	44	0.5%	38	0.9%
DC	7	0.2%	31	0.3%	41	0.9%
DD, DH, DN	274	6.0%	1822.6	19.9%	529	12.1%
DE	18	0.4%	22	0.2%	34	0.8%
DF, DG	746	16.3%	277	3.0%	442	10.1%
DI	30	0.7%	78	0.9%	73	1.7%
DJ	181	4.0%	452	4.9%	360	8.2%
DK, DL, DM	1621.888	35.4%	4586.6	50.1%	1652	37.7%
E	37	0.8%	13	0.1%	14	0.3%
F	55	1.2%	76	0.8%	49	1.1%
G	144	3.1%	319	3.5%	196	4.5%
H	7	0.2%	1	0.0%	3	0.1%
I	57	1.2%	30	0.3%	50	1.1%
J	25	0.5%	196	2.1%	45	1.0%
K	1083.334	23.7%	1058	11.6%	673.2	15.4%
L	3	0.1%	0	0.0%	0	0.0%
M	3	0.1%	4	0.0%	24	0.5%
N	0	0.0%	0	0.0%	2	0.0%
O	58	1.3%	41	0.4%	26	0.6%
P	0	0.0%	0	0.0%	0	0.0%
Total	4578.2		9148.2		4379.2	

Table 4 - Regional distribution of environmental technologies 2002-2004

	WIPO IPC	%	OECD EnvTech	%	EPO ECLAY02	%
ITC1	734.422	16.0%	3084	33.7%	618	14.1%
ITC2	3	0.1%	19	0.2%	5	0.1%
ITC3	247	5.4%	174	1.9%	170	3.9%
ITC4	1746	38.1%	2664	29.1%	1638	37.4%
ITF1	26	0.6%	42	0.5%	28	0.6%
ITF2	0	0.0%	6	0.1%	4	0.1%
ITF3	39	0.9%	116	1.3%	40	0.9%
ITF4	55	1.2%	102	1.1%	38	0.9%
ITF5	5	0.1%	14	0.2%	5	0.1%
ITF6	17	0.4%	0	0.0%	2	0.0%
ITG1	104	2.3%	93	1.0%	96	2.2%
ITG2	12	0.3%	9	0.1%	7	0.2%
ITH1, ITH2	38	0.8%	46	0.5%	46	1.1%
ITH3	349	7.6%	731	8.0%	471	10.8%
ITH4	106	2.3%	96	1.0%	139	3.2%
ITH5	458.8	10.0%	1332.2	14.6%	588.2	13.4%
ITI1	229	5.0%	275	3.0%	178	4.1%
ITI2	28	0.6%	18	0.2%	30	0.7%
ITI3	107	2.3%	71	0.8%	97	2.2%
ITI4	274	6.0%	256	2.8%	179	4.1%
Total	4578.2		9148.2		4379.2	

Table 5 - Description of variables and descriptive statistics

Variable	Description	N	Mean	sd	Min	Max
GT	Natural logarithm of the average of the cumulative count of green technologies in Region i and Sector j in the years 2002 to 2004 on full time equivalent jobs 2002-2004 (source: PATSTAT, Orbis)	199	0.22	0.41	0	1.96
W*GT	Natural logarithm of GT generated by sectors j weighted by a weighting matrix W built according to the vertical relatedness among sectors in 2002-2004 (source: PATSTAT, AIDA and Input Output Tables by ISTAT)	199	0.15	0.30	0	1.56
EP_AC	Emission intensity of Acidifying Gases (mainly NOx, SOx and NH3), given by the natural logarithm of the ratio between AC and the real value added of Region i, Sector j in 2005 (source: Regional NAMEA and ISTAT)	199	3.49	1.58	-0.80	6.06
EP_CO2	Emission productivity of CO2, given by the natural logarithm of the ratio between real value added and CO2 of Region i, Sector j, in t-1 (source: Regional NAMEA and ISTAT)	199	0.54	1.52	-3.24	3.25
EP_GHG	Emission productivity of Greenhouse Gases (mainly CO2, CH4 and N2O), given by the natural logarithm of the ratio between real value added and GHG of Region i, Sector j in 2005 (source: Regional NAMEA and ISTAT)	199	0.47	1.51	-3.26	3.21
METRO	Presence of Metropolitan Areas in the Region. Equal to one in the presence of Milan, Neaples, Rome andTurin	199	0.20	0.40	0	1
DENSITY	Given by the ratio of mean population in the Region i on the area of i in 2002-2004 (source: ISTAT)	199	-1.92	0.63	-3.29	-0.86
ENERGY	Natural Logarithm of the ratio between mean Energy Consumption of Sector j in 2004 and its mean value added in 2004 (source: TERNA)	199	-5.42	1.80	-10.92	-2.35
EXPORT	Natural Logarithm of the ratio between average Export (within European Union) 2002-2004 and mean value added 2002-2004. (source: ISTAT)	199	4.91	0.77	2.37	5.76
POL	Natural Logarithm of the ratio between average expenditure for environmental protection (only capital expenditure) in 2004 of Region i and the mean value added of Region i in 2004 (source: ISTAT)	199	-6.24	1.20	-8.60	-4.34
LP	Labour productivity measured as the natural logarithm of real value added divided by total employees in 2002-2004 (source: ISTAT)	199	3.79	0.57	2.73	5.34
DIRTY	DIRTY is equal to one for strongly polluting sectors, i.e. DF, DG, DI and E [Nace Revision 1.1]: Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of chemicals, chemical products and man-made fibres; manufacture of other non-metallic mineral products and Energy, water and gas supply.	199	0.30	0.46	0	1
NORTHW	Locational variables for northern-western Regions	199	0.20	0.40	0	1
NORTHE	Locational variables for northern-eastern Regions	199	0.20	0.40	0	1
CENTRE	Locational variables for central and Regions	199	0.20	0.40	0	1
SOUTH	Locational variables for northern southern Regions	199	0.40	0.49	0	1

Descriptivestatisticsfor GT and WGT refertogreentechnologiesassignedusingthe WIPO IPC Classification

Table 6 - Spearman correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	GT	1															
2	W*GT	0.9994*	1														
3	EP_GHG	0.0958	0.0965	1													
4	EP_AC	0.0655	0.0640	0.8769*	1												
5	EP_CO2	0.0860	0.0868	0.9936*	0.8771*	1											
6	LP	0.3339*	0.3320*	-0.3490*	-0.2707*	-0.3241*	1										
7	ENERGY	0.2796*	0.2826*	-0.1270	-0.0606	-0.1090	0.5422*	1									
8	METRO	0.2219*	0.2173*	0.0819	0.1004	0.0808	0.0980	-0.0251	1								
9	DENSITY	0.3281*	0.3256*	0.0726	0.0869	0.0593	0.0666	-0.0791	0.5857*	1							
10	POL	-0.3471*	-0.3463*	-0.0377	-0.1378	-0.0269	-0.1867*	-0.0774	-0.1923*	-0.5974*	1						
11	EXPORT	0.2409*	0.2434*	-0.0001	0.0805	0.0052	0.3020*	0.3007*	-0.0219	0.0208	-0.5025*	1					
12	DIRTY	0.1345	0.1342	-0.6275*	-0.6157*	-0.5995*	0.6839*	0.1630*	-0.0016	-0.0054	0.0049	-0.0009	1				
13	NORTHW	0.1843*	0.1823*	0.0718	0.1179	0.0732	0.1644*	0.0154	0.3841*	0.1721*	-0.0375	0.1567*	0.0067	1			
14	NORTHE	0.1102	0.1136	-0.0271	-0.0594	-0.0227	0.1923*	0.1078	-0.2516*	-0.0044	-0.1268	0.5857*	-0.0016	-0.2476*	1		
15	CENTRE	0.0701	0.0701	0.0945	0.0801	0.0880	0.0262	-0.0129	0.0613	0.0612	-0.4327*	-0.0022	-0.0016	-0.2476*	-0.2516*	1	
16	SOUTH	-0.2966*	-0.2977*	-0.1133	-0.1124	-0.1126	-0.3117*	-0.0901	-0.1555*	-0.1858*	0.4877*	-0.6038*	-0.0027	-0.4048*	-0.4112*	-0.4112*	1

GT and WGT refertogreentechnologiesassignedusingthe WIPO IPC Classification

Table 7 – Econometric results (WIPO Green Inventory)

	(1) lnCO2	(2) lnGHG	(3) lnAC	(4) lnCO2	(5) lnGHG	(6) lnAC
GT	0.6538***	0.5998***	0.3019			
	(0.1980)	(0.2024)	(0.1848)			
W*GT				0.8344***	0.7567***	0.3259
				(0.2680)	(0.2743)	(0.2487)
LP	-0.1137	-0.0694	0.4523**	-0.0942	-0.0496	0.4663**
	(0.2043)	(0.2088)	(0.1906)	(0.2055)	(0.2103)	(0.1907)
DENSITY	0.2811*	0.2418	0.1875	0.2838*	0.2433	0.1910
	(0.1616)	(0.1652)	(0.1508)	(0.1627)	(0.1665)	(0.1510)
POL	0.1129	0.1003	-0.0409	0.1122	0.1001	-0.0438
	(0.1146)	(0.1171)	(0.1069)	(0.1155)	(0.1181)	(0.1071)
EXPORT	-0.0874	-0.0911	0.0925	-0.0850	-0.0892	0.0933
	(0.1470)	(0.1503)	(0.1372)	(0.1482)	(0.1516)	(0.1375)
DIRTY	-2.4929***	-2.5148***	-3.2504***	-2.5054***	-2.5251***	-3.2597***
	(0.2470)	(0.2525)	(0.2305)	(0.2492)	(0.2550)	(0.2313)
NORTHW	0.3082	0.2895	-0.0019	0.3177	0.3019	0.0189
	(0.2333)	(0.2385)	(0.2177)	(0.2348)	(0.2402)	(0.2179)
NORTHE	0.2676	0.2407	-0.3026	0.2758	0.2491	-0.2915
	(0.2509)	(0.2565)	(0.2342)	(0.2526)	(0.2585)	(0.2344)
CENTRE	0.5938**	0.5486**	0.0819	0.6003**	0.5536**	0.0930
	(0.2516)	(0.2572)	(0.2348)	(0.2533)	(0.2592)	(0.2351)
_cons	3.0017***	2.7001***	2.3787**	2.9329***	2.6342**	2.3199**
	(0.9860)	(1.0080)	(0.9201)	(0.9926)	(1.0157)	(0.9211)
N	199	199	199	199	199	199
R^2	0.576	0.560	0.658	0.571	0.554	0.658
adj. R^2	0.5561	0.5392	0.6415	0.5505	0.5327	0.6414

Huber-White Robust Standard errors in parentheses
The estimations have been carried out on the ATECO sectors D and E
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8 - Econometric Results (OECD Env Tech)

	(1)	(2)	(3)	(4)	(5)	(6)
	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC
GT	0.5092***	0.4736***	0.2134			
	(0.1732)	(0.1772)	(0.1601)			
W*GT				0.6101***	0.5783**	0.2591
				(0.2328)	(0.2374)	(0.2128)
LP	-0.0333	0.0270	0.5105***	-0.0052	0.0323	0.5058***
	(0.2043)	(0.2091)	(0.1888)	(0.2069)	(0.2109)	(0.1890)
DENSITY	0.2748*	0.2208	0.1754	0.2599	0.2231	0.1815
	(0.1622)	(0.1660)	(0.1499)	(0.1642)	(0.1674)	(0.1501)
POL	0.0978	0.0878	-0.0522	0.0911	0.0845	-0.0519
	(0.1149)	(0.1176)	(0.1062)	(0.1163)	(0.1186)	(0.1063)
EXPORT	-0.1309	-0.1359	0.0769	-0.1313	-0.1327	0.0810
	(0.1480)	(0.1515)	(0.1368)	(0.1498)	(0.1527)	(0.1369)
DIRTY	-2.4181***	-2.4468***	-3.2673***	-2.4085***	-2.4490***	-3.2605***
	(0.2470)	(0.2528)	(0.2283)	(0.2502)	(0.2550)	(0.2286)
NORTHW	0.2813	0.2654	0.0138	0.3088	0.2690	0.0159
	(0.2375)	(0.2431)	(0.2195)	(0.2411)	(0.2458)	(0.2203)
NORTHE	0.2777	0.2545	-0.2876	0.2841	0.2600	-0.2813
	(0.2526)	(0.2585)	(0.2334)	(0.2556)	(0.2605)	(0.2335)
CENTRE	0.6204**	0.5787**	0.1183	0.6289**	0.5792**	0.1230
	(0.2524)	(0.2583)	(0.2333)	(0.2556)	(0.2606)	(0.2336)
_cons	2.7881***	2.4168**	2.1381**	2.6188***	2.3819**	2.1507**
	(0.9885)	(1.0117)	(0.9136)	(1.0009)	(1.0204)	(0.9146)
N	199	199	199	199	199	199
R^2	0.571	0.551	0.665	0.557	0.545	0.664
adj. R^2	0.5504	0.5294	0.6490	0.5357	0.5235	0.6480

Huber-White Robust Standard errors in parentheses
The estimations have been carried out on the ATECO sectors D and E
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 - Econometric results (ECLA Y02)

	(1) lnCO2	(2) lnGHG	(3) lnAC	(4) lnCO2	(5) lnGHG	(6) lnAC
GT	0.7345***	0.6682***	0.3304*			
	(0.2055)	(0.2102)	(0.1954)			
W*GT				0.9212***	0.7874***	0.4049
				(0.2866)	(0.2961)	(0.2699)
LP	-0.0505	-0.0099	0.4757**	-0.0351	0.0395	0.4807**
	(0.1987)	(0.2032)	(0.1889)	(0.2011)	(0.2077)	(0.1894)
DENSITY	0.2729*	0.2344	0.1772	0.2739*	0.2103	0.1818
	(0.1579)	(0.1615)	(0.1501)	(0.1598)	(0.1650)	(0.1505)
POL	0.1090	0.0929	-0.0415	0.1051	0.0908	-0.0422
	(0.1118)	(0.1144)	(0.1063)	(0.1132)	(0.1170)	(0.1066)
EXPORT	-0.1082	-0.1149	0.0974	-0.1012	-0.1123	0.1016
	(0.1435)	(0.1468)	(0.1364)	(0.1452)	(0.1500)	(0.1367)
DIRTY	-2.5457***	-2.5697***	-3.2591***	-2.5447***	-2.5522***	-3.2652***
	(0.2425)	(0.2481)	(0.2306)	(0.2458)	(0.2539)	(0.2315)
NORTHW	0.2387	0.2167	-0.0382	0.2494	0.2602	-0.0277
	(0.2309)	(0.2362)	(0.2196)	(0.2342)	(0.2419)	(0.2206)
NORTHE	0.1798	0.1613	-0.3365	0.1865	0.1813	-0.3272
	(0.2488)	(0.2545)	(0.2365)	(0.2518)	(0.2601)	(0.2371)
CENTRE	0.5639**	0.5260**	0.0865	0.5700**	0.5380**	0.0919
	(0.2454)	(0.2510)	(0.2333)	(0.2484)	(0.2566)	(0.2339)
_cons	2.8542***	2.5532**	2.2356**	2.7550***	2.3051**	2.2105**
	(0.9597)	(0.9817)	(0.9125)	(0.9715)	(1.0035)	(0.9149)
N	199	199	199	199	199	199
R^2	0.596	0.580	0.661	0.585	0.555	0.661
adj. R^2	0.5763	0.5597	0.6454	0.5655	0.5341	0.6444

Huber-White Robust Standard errors in parentheses
The estimations have been carried out on the ATECO sectors D and E
$^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table 10 - Robustness check (Equation (7))

	WIPO Inventory Method			OECD Env Tech			ECLA Y02		
	(4a)	(5a)	(6a)	(4b)	(5b)	(6b)	(4c)	(5c)	(6c)
	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC
W*GT	0.8076***	0.7257**	0.3810	0.5667**	0.5519**	0.2959	0.9435***	0.8185***	0.4844*
	(0.2777)	(0.2842)	(0.2556)	(0.2413)	(0.2458)	(0.2178)	(0.2934)	(0.3019)	(0.2756)
LP	-0.1771	-0.1049	0.5352**	-0.1159	-0.0365	0.6390***	-0.0557	-0.0199	0.5698**
	(0.2522)	(0.2580)	(0.2321)	(0.2564)	(0.2612)	(0.2315)	(0.2481)	(0.2553)	(0.2330)
DENSITY	0.1857	0.1215	0.1468	0.2110	0.1806	0.1892	0.1836	0.1367	0.1302
	(0.2232)	(0.2284)	(0.2055)	(0.2255)	(0.2297)	(0.2036)	(0.2177)	(0.2241)	(0.2045)
ENERGY	0.0282	0.0242	-0.0358	0.0395	0.0235	-0.0475	-0.0005	0.0084	-0.0419
	(0.0556)	(0.0569)	(0.0512)	(0.0559)	(0.0569)	(0.0504)	(0.0539)	(0.0555)	(0.0507)
METRO	0.1780	0.1943	0.0984	0.0961	0.0805	0.0012	0.1647	0.1597	0.1081
	(0.2880)	(0.2947)	(0.2651)	(0.2930)	(0.2984)	(0.2645)	(0.2809)	(0.2891)	(0.2639)
POL	0.0673	0.0527	-0.0480	0.0579	0.0590	-0.0371	0.0725	0.0548	-0.0454
	(0.1307)	(0.1337)	(0.1203)	(0.1324)	(0.1349)	(0.1195)	(0.1275)	(0.1312)	(0.1198)
EXPORT	-0.1443	-0.1481	0.1103	-0.1837	-0.1686	0.1214	-0.1310	-0.1470	0.1242
	(0.1666)	(0.1705)	(0.1534)	(0.1675)	(0.1706)	(0.1513)	(0.1619)	(0.1666)	(0.1521)
DIRTY	-2.4348***	-2.4521***	-3.3310***	-2.3270***	-2.3971***	-3.3905***	-2.5351***	-2.5309***	-3.3492***
	(0.2744)	(0.2807)	(0.2526)	(0.2733)	(0.2784)	(0.2467)	(0.2690)	(0.2768)	(0.2527)
NORTHW	0.3073	0.2960	-0.0529	0.3366	0.2819	-0.0437	0.1955	0.2063	-0.1189
	(0.2535)	(0.2594)	(0.2334)	(0.2580)	(0.2628)	(0.2330)	(0.2511)	(0.2584)	(0.2359)
NORTHE	0.3402	0.3151	-0.2994	0.3423	0.2985	-0.3227	0.2156	0.2129	-0.3473
	(0.2693)	(0.2755)	(0.2479)	(0.2734)	(0.2784)	(0.2468)	(0.2676)	(0.2754)	(0.2514)
CENTRE	0.5711**	0.5210*	0.0664	0.6182**	0.5682**	0.1151	0.5282**	0.4986*	0.0594
	(0.2647)	(0.2708)	(0.2437)	(0.2670)	(0.2720)	(0.2411)	(0.2580)	(0.2655)	(0.2424)
Cons	3.1635**	2.6713*	1.6793	3.1561**	2.6686*	1.3465	2.5775*	2.3487*	1.4295
	(1.3980)	(1.4305)	(1.2870)	(1.4079)	(1.4341)	(1.2713)	(1.3659)	(1.4055)	(1.2831)
N	199	199	199	199	199	199	199	199	199
R^2	0.566	0.544	0.660	0.552	0.541	0.672	0.585	0.561	0.664
adj. R^2	0.5401	0.5168	0.6405	0.5261	0.5140	0.6524	0.5608	0.5355	0.6437

Huber-White Robust Standard errors in parentheses

The estimations have been carried out on the NACE sectors D and E

$^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table 11- Robustness Check (relatedness matrix cutoff 0.75)

	WIPO Green Inventory						OECD Environmental Technologies						ECLA Y02					
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(1c)	(2c)	(3c)	(4c)	(5c)	(6c)
	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC	lnCO2	lnGHG	lnAC
GT	0.6538***	0.5998***	0.3019				0.5092***	0.4736***	0.2134				0.7345***	0.6682***	0.3304*			
	(0.1980)	(0.2024)	(0.1848)				(0.1732)	(0.1772)	(0.1601)				(0.2055)	(0.2102)	(0.1954)			
W*GT				0.8344***	0.7567***	0.3259				0.6101***	0.5783**	0.2591				0.9212***	0.7874***	0.4049
				(0.2680)	(0.2743)	(0.2487)				(0.2328)	(0.2374)	(0.2128)				(0.2866)	(0.2961)	(0.2699)
LP	-0.1137	-0.0694	0.4523**	-0.0942	-0.0496	0.4663**	-0.0333	0.0270	0.5105***	-0.0052	0.0323	0.5058***	-0.0505	-0.0099	0.4757**	-0.0351	0.0395	0.4807**
	(0.2043)	(0.2088)	(0.1906)	(0.2055)	(0.2103)	(0.1907)	(0.2043)	(0.2091)	(0.1888)	(0.2069)	(0.2109)	(0.1890)	(0.1987)	(0.2032)	(0.1889)	(0.2011)	(0.2077)	(0.1894)
DENSITY	0.2811*	0.2418	0.1875	0.2838*	0.2433	0.1910	0.2748*	0.2208	0.1754	0.2599	0.2231	0.1815	0.2729*	0.2344	0.1772	0.2739*	0.2103	0.1818
	(0.1616)	(0.1652)	(0.1508)	(0.1627)	(0.1665)	(0.1510)	(0.1622)	(0.1660)	(0.1499)	(0.1642)	(0.1674)	(0.1501)	(0.1579)	(0.1615)	(0.1501)	(0.1598)	(0.1650)	(0.1505)
POL	0.1129	0.1003	-0.0409	0.1122	0.1001	-0.0438	0.0978	0.0878	-0.0522	0.0911	0.0845	-0.0519	0.1090	0.0929	-0.0415	0.1051	0.0908	-0.0422
	(0.1146)	(0.1171)	(0.1069)	(0.1155)	(0.1181)	(0.1071)	(0.1149)	(0.1176)	(0.1062)	(0.1163)	(0.1186)	(0.1063)	(0.1118)	(0.1144)	(0.1063)	(0.1132)	(0.1170)	(0.1066)
EXPORT	-0.0874	-0.0911	0.0925	-0.0850	-0.0892	0.0933	-0.1309	-0.1359	0.0769	-0.1313	-0.1327	0.0810	-0.1082	-0.1149	0.0974	-0.1012	-0.1123	0.1016
	(0.1470)	(0.1503)	(0.1372)	(0.1482)	(0.1516)	(0.1375)	(0.1480)	(0.1515)	(0.1368)	(0.1498)	(0.1527)	(0.1369)	(0.1435)	(0.1468)	(0.1364)	(0.1452)	(0.1500)	(0.1367)
DIRTY	-2.4929***	-2.5148***	-3.2504***	-2.5054***	-2.5251***	-3.2597***	-2.4181***	-2.4468***	-3.2673***	-2.4085***	-2.4490***	-3.2605***	-2.5457***	-2.5697***	-3.2591***	-2.5447***	-2.5522***	-3.2652***
	(0.2470)	(0.2525)	(0.2305)	(0.2492)	(0.2550)	(0.2313)	(0.2470)	(0.2528)	(0.2283)	(0.2502)	(0.2550)	(0.2286)	(0.2425)	(0.2481)	(0.2306)	(0.2458)	(0.2539)	(0.2315)
NORTHW	0.3082	0.2895	-0.0019	0.3177	0.3019	0.0189	0.2813	0.2654	0.0138	0.3088	0.2690	0.0159	0.2387	0.2167	-0.0382	0.2494	0.2602	-0.0277
	(0.2333)	(0.2385)	(0.2177)	(0.2348)	(0.2402)	(0.2179)	(0.2375)	(0.2431)	(0.2195)	(0.2411)	(0.2458)	(0.2203)	(0.2309)	(0.2362)	(0.2196)	(0.2342)	(0.2419)	(0.2206)
NORTHE	0.2676	0.2407	-0.3026	0.2758	0.2491	-0.2915	0.2777	0.2545	-0.2876	0.2841	0.2600	-0.2813	0.1798	0.1613	-0.3365	0.1865	0.1813	-0.3272
	(0.2509)	(0.2565)	(0.2342)	(0.2526)	(0.2585)	(0.2344)	(0.2526)	(0.2585)	(0.2334)	(0.2556)	(0.2605)	(0.2335)	(0.2488)	(0.2545)	(0.2365)	(0.2518)	(0.2601)	(0.2371)
CENTRE	0.5938**	0.5486**	0.0819	0.6003**	0.5536**	0.0930	0.6204**	0.5787**	0.1183	0.6289**	0.5792**	0.1230	0.5639**	0.5260**	0.0865	0.5700**	0.5380**	0.0919
	(0.2516)	(0.2572)	(0.2348)	(0.2533)	(0.2592)	(0.2351)	(0.2524)	(0.2583)	(0.2333)	(0.2556)	(0.2606)	(0.2336)	(0.2454)	(0.2510)	(0.2333)	(0.2484)	(0.2566)	(0.2339)
Constant	3.0017***	2.7001***	2.3787**	2.9329***	2.6342**	2.3199**	2.7881***	2.4168**	2.1381**	2.6188***	2.3819**	2.1507**	2.8542***	2.5532**	2.2356**	2.7550***	2.3051**	2.2105**
	(0.9860)	(1.0080)	(0.9201)	(0.9926)	(1.0157)	(0.9211)	(0.9885)	(1.0117)	(0.9136)	(1.0009)	(1.0204)	(0.9146)	(0.9597)	(0.9817)	(0.9125)	(0.9715)	(1.0035)	(0.9149)
N	199	199	199	199	199	199	199	199	199	199	199	199	199	199	199	199	199	199
R^2	0.576	0.560	0.658	0.571	0.554	0.658	0.571	0.551	0.665	0.557	0.545	0.664	0.596	0.580	0.661	0.585	0.555	0.661
adj. R^2	0.5561	0.5392	0.6415	0.5505	0.5327	0.6414	0.5504	0.5294	0.6490	0.5357	0.5235	0.6480	0.5763	0.5597	0.6454	0.5655	0.5341	0.6444

Huber-White Robust Standard errors in parentheses

The estimations have been carried out on the NACE sectors D and E

$^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table 12 – Robustness check: IV estimation

	(1) lnCO2	(2) lnGHG	(3) lnAC	(4) lnCO2	(5) lnGHG	(6) lnAC
GT	0.3799*	0.3637*	0.1631			
	(0.2015)	(0.2154)	(0.2364)			
W*GT				0.5515**	0.5166*	0.2564
				(0.2698)	(0.2923)	(0.3163)
LP	0.1785	0.1049	0.4869	0.1849	0.1106	0.4905
	(0.3119)	(0.2861)	(0.3074)	(0.3112)	(0.2856)	(0.3073)
DENSITY	-0.1163	-0.0843	-0.2433	-0.1162	-0.0839	-0.2439
	(0.2345)	(0.2314)	(0.2345)	(0.2349)	(0.2319)	(0.2348)
POL	0.0503	0.0312	-0.1243	0.0531	0.0333	-0.1221
	(0.1288)	(0.1256)	(0.1318)	(0.1291)	(0.1258)	(0.1321)
ENERGY	0.0302	0.0320	0.0265	0.0288	0.0312	0.0251
	(0.0760)	(0.0747)	(0.0767)	(0.0760)	(0.0747)	(0.0768)
METRO	0.3658	0.3140	0.3982	0.3689	0.3168	0.3997
	(0.2702)	(0.2706)	(0.2606)	(0.2699)	(0.2711)	(0.2608)
EXPORT_UE	-0.1829	-0.1960	-0.0538	-0.1790	-0.1929	-0.0510
	(0.1688)	(0.1646)	(0.1677)	(0.1688)	(0.1647)	(0.1676)
DIRTY	-2.3417***	-2.3659***	-2.8082***	-2.3567***	-2.3784***	-2.8180***
	(0.2604)	(0.2592)	(0.2777)	(0.2609)	(0.2597)	(0.2782)
NORDW	0.4246	0.4287	0.2051	0.4185	0.4250	0.1988
	(0.2933)	(0.2865)	(0.3030)	(0.2936)	(0.2868)	(0.3031)
NORDE	0.4623	0.4335	-0.0661	0.4620	0.4342	-0.0680
	(0.2935)	(0.2714)	(0.2850)	(0.2930)	(0.2710)	(0.2840)
CENTRE	0.5858**	0.5770**	0.1299	0.5856**	0.5774**	0.1287
	(0.2492)	(0.2429)	(0.2406)	(0.2491)	(0.2428)	(0.2402)
_cons	1.2688	1.5269	1.4876	1.2402	1.5045	1.4666
	(1.6886)	(1.6190)	(1.5638)	(1.6885)	(1.6195)	(1.5660)
N	199	199	199	199	199	199
Endogeneity test (Hausman)	0.275	0.207	0.830	0.108	0.201	0.031
p-value	0.6000	0.6492	0.3624	0.7427	0.6538	0.8593
R^2	0.446	0.487	0.503	0.445	0.485	0.502
adj. R^2	0.4138	0.4567	0.4734	0.4128	0.4552	0.4728

Huber-White Robust Standard errors in parentheses

Instrumental variables estimates. GT in 1999-2001 and W*GT in 1999-2001 have been used as instruments for, respectively, GT and W*GT.

Estimations have been carried out on the ATECO sectors D and E

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table A1 Sectoral Classification

Sector NACE REV 1.1	Description
DA	Manufacture of food products, beverages and tobacco
DB	Manufacture of textiles and textile products
DC	Manufacture of leather and leather products
DD, DH, DN	Manufacture of wood and wood products; Manufacture of rubber and plastic products; Other manufacture
DE	Manufacture of pulp, paper and paper products; publishing and printing
DF, DG	Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of chemicals, chemical products and man-made fibers
DI	Manufacture of other non-metallic mineral products
DJ	Manufacture of basic metals and fabricated metal products
DK, DL, DM	Manufacture of machinery and equipment n.e.c.; Manufacture of electrical and optical equipment; Manufacture of transport equipment
E	Electricity, gas and water supply