Environ Econ Policy Stud (2016) 18:247–263
DOI 10.1007/s10018-015-0126-1

RESEARCH ARTICLE

Green Growth, Eco Innovation and Sustainable Transitions

Green inventions and greenhouse gas emission dynamics: a close examination of provincial Italian data

Ding Weina[1] · **Marianna Gilli**[2] · **Massimiliano Mazzanti**[2] · **Francesco Nicolli**[3]

Received: 4 February 2015 / Accepted: 22 August 2015 / Published online: 28 September 2015

Abstract Eco-innovation plays a crucial role in reducing carbon emissions. Exploiting the consolidated IPAT/STIRPAT framework, this paper studies whether a relationship exists between green technological change (measured as stock of green patent) and both CO_2 emissions and emission efficiency (CO_2/VA). To investigate this relation, a rich panel covering 95 Italian provinces from 1990 to 2010 is exploited. The main regression results suggest that green technology has not yet played a significant role in promoting environmental protection, although it improved significantly environmental productivity. Notably, this result is not driven by regional differences, and the main evidence is consistent among different areas of the country.

Keywords CO_2 emission · Technological change · Green patents · IPAT · Environmental performance

JEL Classification Q 53 · Q 55

1 Introduction

Carbon dioxide emissions and the improvement of environmental efficiency in relation to global warming have become urgent issues throughout the world. Over the last two decades, economic growth has been associated with a 44 % increase in

✉ Marianna Gilli
marianna.gilli@unife.it

1 Credit Reference Center, The People's Bank of China, Beijing 100031, China

2 Department of Economics and Management, University of Ferrara, Via Voltapletto 11, Ferrara, Italy

3 IRCrES/CNR, Via Bassini 15, Milan, Italy

CO_2 levels, and only a small number of countries have managed to decrease their emissions during this period.

The advancements in science and technology are considered to be key concerns in addressing environmental issues and confronting climate change (Abbott 2012), but there are several unanswered questions. For instance: “How exactly do technology and innovation affect carbon dioxide emissions?”, “Does technology innovation, especially environmental innovation, positively affect the reduction of emissions?”, and “How can the government act with respect to the policy on relevant innovations?” These are only some examples of questions raised by scholars and policymakers in the last decade.

Most of the literature has relied on firm-level data to test environmental innovation drivers. Among recent contribution, for example, in Berrone et al. (2013), the authors investigate if both institutional pressures and factors internal to the firm’s organisation as well as their interaction, have a positive effect on firm’s propensity to engage in environmental innovation. Based on a sample of 326 firms in the US, they found that institutional pressures can actually enhance eco-innovation adoption in firms, especially when they show higher rates of pollution with respect to the other firms in the sector. Secondly, the authors found that firm’s internal organization matters in terms of assets specificity and resource availability. Similarly, Cai and Zhou (2014) investigated the factors that influence the adoption of eco-innovation in Chinese firms. Their findings highlight that in this country environmental innovation is mainly triggered by pressures external to firms such as customer’s green demand and competitors in the sector. This branch of literature is very extensive, and a survey can be found in Del Río (2009) and Cecere et al. (2014).

Another branch of the environmental innovation literature focused on a sector-level viewpoint. This is a key perspective for two main reasons: first, while innovation occurs within the firm, technological change takes place only at the sector level (Dopfer 2012). Secondly, the sectorial level allows a more rigorous evaluation of the overall policy implications. Goulder and Schneider (1999) investigates the role of induced technological change on CO_2 abatement expenditure at a sectorial level. The authors found that even if technological change can lower the cost of achieving a certain environmental target, it implies an higher gross cost of a given carbon tax. Del Río et al. (2011), investigated the drivers of environmental innovation on a panel of Spanish industries and concluded that technology investments are positively and strongly related to human and physical capital intensity and R&D and negatively related to the export intensity of sectors. In addition, they found that policy stringency played a relevant role in shaping the investment choices in environmental technologies. The empirical results of Carrión-Flores and Innes (2010), revealed a negative and significant bidirectional linkage between toxic air pollution and environmental innovation, by the estimation of a panel of 127 manufacturing industries over a 16-year period (1989–2004).

A third wave of research on environmental innovation and its effects on the actual reduction of polluting emissions goes beyond the economic agent perspective and considers a geographical viewpoint to discuss issues such as agglomerative effects and spatial features. Costantini et al. (2013) used NAMEA data to investigate the heterogeneous distribution of emissions across Italy. Considering differences in local factors affecting environmental innovation, they found an agglomeration effect that seems to influence environmental performance at a regional level. Moreover, they found that technological and environmental spillovers are relevant for sectorial environmental efficiency and that these factors can drive environmental efficiency more than internal innovation.

From a country perspective, many authors highlighted differences in pollution emissions trends across countries or group of countries. For example, Kim and Kim (2012) studied the CO_2 emission trend in both OECD and non-OECD countries and found that, notwithstanding some variation within the two groups of countries, emissions are decreasing in OECD-countries such as European member states and the US, but they are increasing in countries such as India and China, which are experiencing a great economic growth.

Nevertheless, literature on the effect of technological changes, particularly those aiming to improve environmental conditions, is still rather scarce, particularly concerning regional and local points of view. This paper attempts to fill this research gap by taking a 'local perspective' through empirically testing the data of 95 provinces in Italy over the years 1990–2010. In particular, referring to the IPAT/STIRPAT framework we shed a light on the role played by green technological change on climate change mitigation. In particular we constructed a green patent stock and used it as proxy of technological change and we adopted two different measures of environmental performances, i.e. total CO_2 emission and environmental productivity. The intuition here is that the development of green technologies at provincial level can induce firms to adopt greener production processes which have become less expensive, and this can lead to an overall increase in environmental performances. As a consequence we expect a strong connection between environmental productivity and the stock of green knowledge, the latter being strongly related to productivity. On the contrary we do not have a priori expectation on the effect of technological change on total CO_2 production, given that other factors, like an increase in the scale of the economy or changes in consumption patterns can offset the positive effect of technological change.

The preliminary evidence (at the regional level) presented in Figs. 1 and 2 confirms previous expectations on North–South disparities, with several exceptions. Emissions tend to be more concentrated in more industrialised Northern provinces, while the South tends to produce, on average, less CO_2. Puglia is a relevant exception, being the third highest polluter; similarly, Trentino-Alto Adige, a Northern region, is among the cleanest in the country. In particular, concerning CO_2 emissions, Piemonte, Lombardia and Puglia are the three regions associated with a higher level of total CO_2 production, whereas in the other areas, total emissions are on a homogeneous level. Notably, the regional ranking in regard to emission efficiency (Fig. 2) is fairly similar to that of total emission, but it shows a completely different trend over time. On the one hand, the total CO_2 emission generally increases from 1990 to 2010 (with the exception of year 2010 in full economic crises); on the other hand, emission intensity is significantly decreasing, highlighting an overall gain in environmental efficiencies across Italian regions.

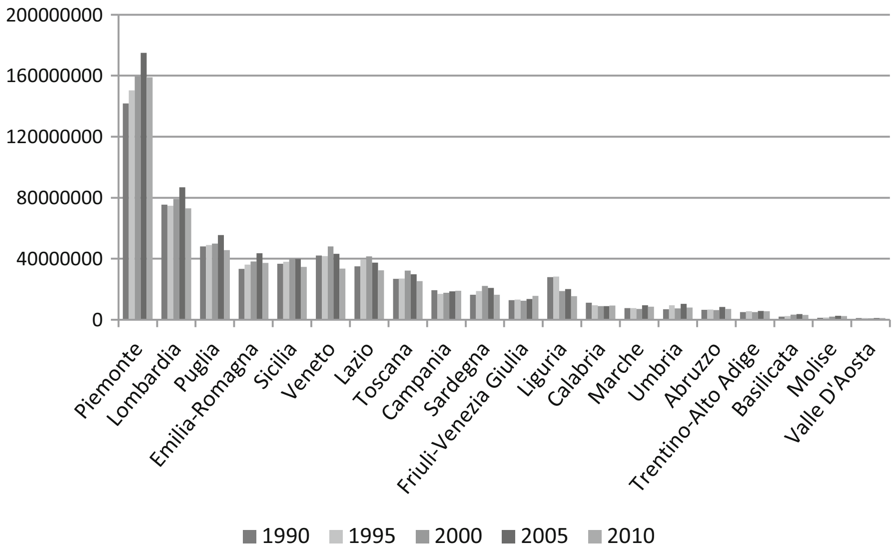

Fig. 1 The CO_2 emission of 20 regions in Italy for five selected years (Unit: Mg)

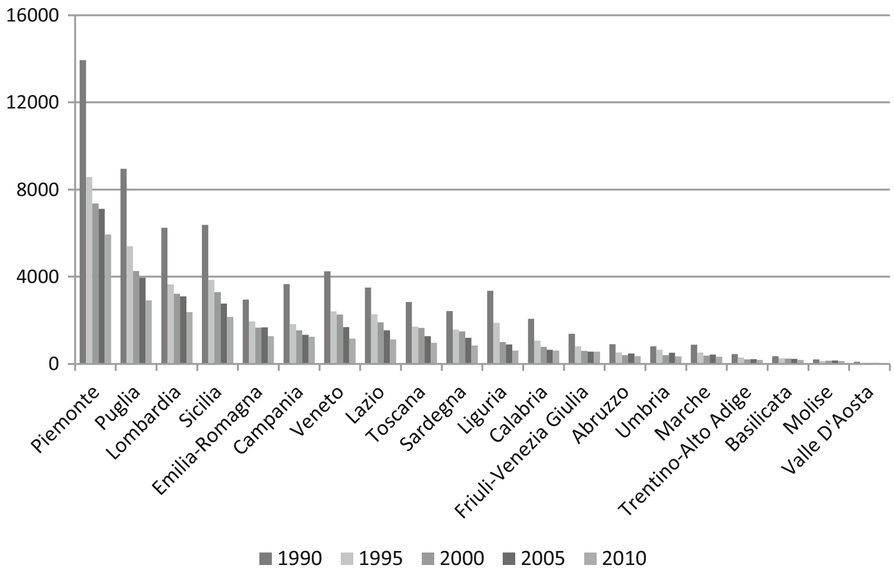

Fig. 2 Emission intensity (CO_2/VA) across 20 regions in Italy for five selected years (Unit: Mg/VA)

Finally, Fig. 3 suggests that the overall increasing trend in green knowledge can be partially correlated to the gain in environmental efficiency, which is constantly increasing over time. Moreover, it should be noted that in the case of green patents, the North–South divide is very evident; patents are more prevalent in Northern

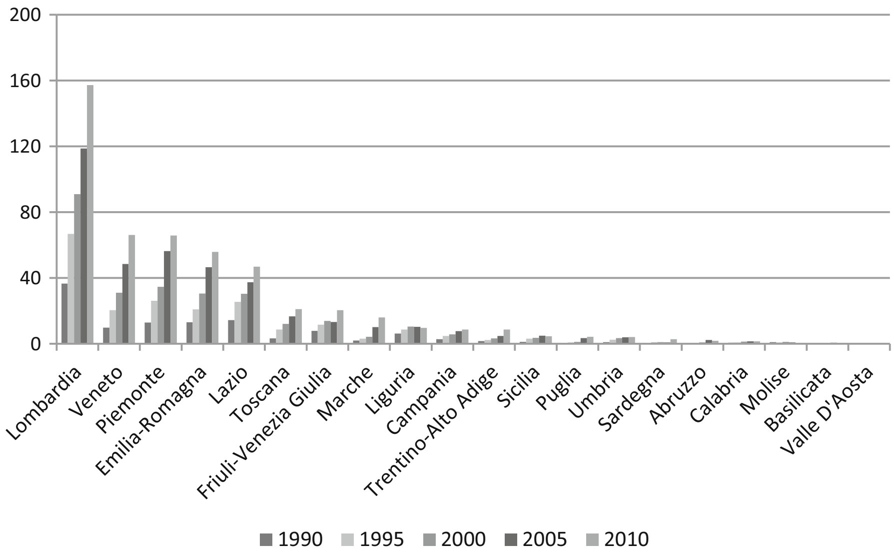

Fig. 3 Green patent stock for 20 Italian regions in the five selected years

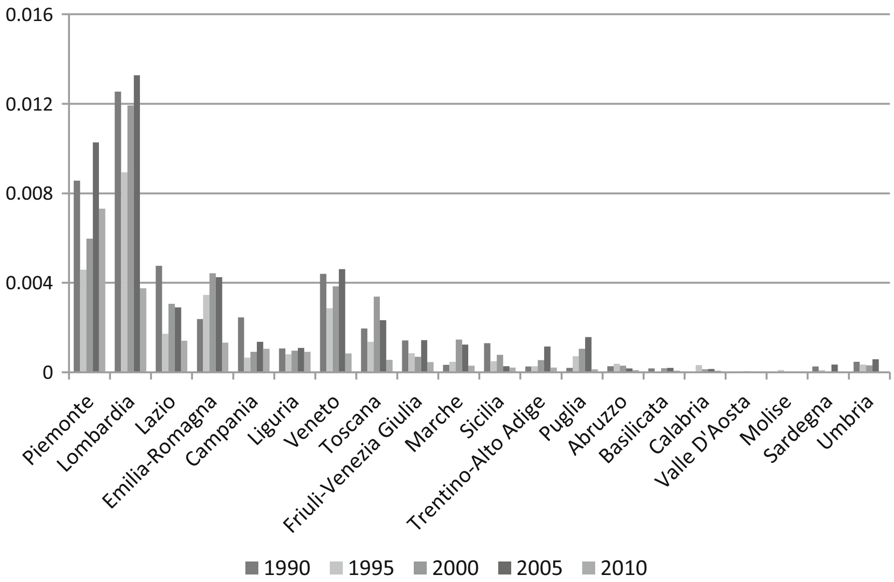

Fig. 4 Number of patents per unit of value added, 20 Italian regions in the five selected years

regions such as Lombardia, Piemonte, Veneto and Emilia-Romagna. These considerations hold also if we scale patent data for provincial Value Added in order to account for differences in the size of Italian provinces (see Fig. 4).

Several reasons justify the choice to conduct a territorial analysis of environmental topics. First, regional frameworks allow for focusing the investigation on structural and idiosyncratic features compared to national averages; second, a disaggregated approach provides useful insights on specific environmental and economic development dynamics, which might be useful for regional policymakers; third, this analysis has political economy implications, which can be differentiated across different regions and territories. This is especially relevant in a country like Italy, which is characterised by high disparities, such as the famous North–South divide. Moreover, it should be noted that this infra-country heterogeneity involves not only economic aspects but also environmental performances, which are highly heterogeneous within the country and tend to favour Northern industrial regions, as confirmed by previous studies based on the national accounting matrix for environmental accounts, known as NAMEA (see Mazzanti and Montini 2010). However, although several works at the national level based on hybrid environmental accounts are well established in the literature (De Haan 2004; Mazzanti and Montini 2010), analysis based on the sub-national/regional level is much rarer.

This paper investigates the role of innovation aimed at reducing carbon dioxide emission as a factor that compensates for economic growth and population growth effects. We test the effect of technology on carbon emissions within a STIRPAT framework, using Italian provincial data covering all 95 provinces over the period 1990–2010. Data are collected every 5 years during this period.

We first conduct the empirical analysis on the entire Italian territory, which is subsequently divided in two sub-samples that characterise the Northern Italian regions and the Southern Italian regions; the aim is to determine the different effects of the environmental innovation adoption on CO_2 emissions taking into account the Italian North–South divide.

Our main finding is that the stock of green patents did not exert a significant effect on CO_2 reduction; on the contrary, it had a significant and positive effect on environmental productivity (CO_2/VA). Notably, this effect seems stronger in the Southern regions, suggesting that some technological effect is also emerging in that part of the country.

The remainder of the paper is organised as follows: Sect. 2 presents emissions' main driving forces; Sect. 3 describes the empirical approach; Sect. 4 discusses the main results; and Sect. 5 concludes.

2 Driving forces

Contributions to literature in this field have discussed the main forces that drive CO_2 emissions in specific countries, such as in Great Britain (Kwon 2005), China (Chong et al. 2012; Feng et al. 2012; Liu et al. 2012), OECD countries (Kerr and Mellon 2012), ASEAN countries (Borhan et al. 2012), and the former Soviet Union (Brizga et al. 2013). Some of these empirical analyses have applied the IPAT framework to build a model for polluting emissions (e.g.: Kwon 2005; MacKellar et al. 1995). Results have shown that many factors affect CO_2 emissions, such as economic scale, population, industrial structure, energy consumption structure and the level of technology and management (Kaya 1990).

The following paragraphs will explain the most relevant factors in depth.

2.1 Population

Population has been found to play a significant role in determining emission levels; in a paper by Dietz and Rosa (1997), who developed a stochastic version of the IPAT model, they concluded that there are diseconomies of scale for the most populated nations that are not consistent with the assumption of direct proportionality (log-linear effects) common to most previous researches. Shi (2003), in a cross country analysis covering 93 different states, has shown that the effect of income on carbon dioxide emission varies across country groups, and that lower income countries have greater elasticity on population. A similar result is obtained by Cole and Neumayer (2004). Dietz and Rosa (1997) and York et al. (2003) found that the elasticity of a population with respect to income is less than 1, in the context of the IPAT model. Finally, researchers working with micro-level data have shown that activities such as transport and residential energy consumption vary according to age structure and household size (e.g., O'Neill and Chen 2002; Liddle 2004; Prskawetz et al. 2004; Zagheni 2011). Recently, studies using cross-country, macro-level data have shown a similar relationship (e.g., Liddle and Lung 2010).

2.2 Affluence

According to York et al. (2003), affluence can be defined as either per capita production or per capita consumption. Dietz and Rosa (1997) predicted that population and economic growth would exacerbate the problem of greenhouse gas (GHG) emission and estimated that the effects of affluence on CO_2 emissions would reach a maximum at approximately $10,000 measured in per capita GDP and would decline at higher levels of affluence. Fan et al. (2006) found that the effect of GDP per capita on total CO_2 emissions is greater for low income countries and found that the effect of energy intensity is strong in upper middle income countries by estimating the same model from different income levels.

The role of affluence, as an indicator of economic growth has been first introduced with Environmental Kuznets Curve (EKC), a model which considers the connection between environmental degradation and economic growth (Grossman and Krueger 1995). EKC shows that, the relation between economic growth and environmental degradation has an inverted U shape. This strand of literature highlight as there are three different driving forces behind this relationship: technology, composition and scale of the economy. The adoption of green technologies, increasing the environmental productivity of firms, tend to promote the emergence of a turning point in the relationship between economic growth and environmental degradation, similarly the shift towards a service society could also be able to foster a process of transition towards a greener society. On the contrary, an increase in the scale of the economy could slow down this process. For a recent review of this topic see Carson (2010).

Differently from this representation, the IPAT framework does not impose any shape on the relation between economic growth and environmental impacts.

2.3 Technology

Green technology is meant to play a central role in reducing the environmental effect of CO_2 emissions and of other pollutants and to simultaneously enhance economic growth. However, although the economic effects of environmental innovations can be related to the economic effects of a more general type of innovation, there remains a lack of evidence on the effects that green technologies can exert on CO_2 emissions. Recently, Wang et al. (2012), who investigated the relationship between innovation in the energy technology sector (proxied by the stock of patents) and CO_2 emission in China, found that innovations that are oriented toward carbon-free technologies can significantly help lower CO_2 level in China. In Gilli et al. (2014), where the complementarity between environmental innovations and general innovation is investigated, results shows that at least in the European manufacturing sector, the joint adoption of eco-innovation and product innovation can considerably affect environmental performance.

A frequent problem researchers face is the measurement of technology stock; several indexes have been developed and used since 1990, which include research expenditure, the amount of the research staff and patent data. Finally, some contributions have measured eco-innovation or other types of innovation through questionnaire surveys (e.g., Anton et al. 2004; Christmann 2000). Among these measures, patent applications are particularly appealing for researchers for many reasons.

First, patent data are easily available in terms of both time and country coverage, and second, they can be easily and efficiently related to technological fields. Each patent is, in fact, classified through an International Patent Classification (IPC) code, developed by the World Intellectual Property Organisation. This tree-like classification allows for creating technological fields at different levels of detail. For example, Section "D" contains all patents related to "textiles; papers", and the subcategory "D 21" refers more specifically to "paper making and production of cellulose", "D 21 F" refers to "Paper making machines; methods of producing paper thereon", and, at the maximum level of detail, "D 21 F 11/06" refers to the hyper-specific field of patents related to "Processes for making continuous lengths of paper, or of cardboard, or of wet web for fibreboard production, on paper-making machines of the cylinder type".

This coding allows for the creation of specific technological subcategories to identify specific fields of interest. For these reasons, patent data have long been considered a useful indicator of innovation for economic research (Griliches 1990). Moreover, as Dernis and Kahn (2004) suggested, in general, all the relevant inventions in economic terms are patented, and for this reason, patents may be used as a valuable indicator of innovative activities by firms, sectors or countries.

Nevertheless, patents also suffer from well-known criticalities. First, it is difficult to discern the value of different patents. An indicator created as the sum of patent counts per year by country certainly includes patents with a high commercial and/or technological effect and a patent with a lower value. Second, patent regimes and patent attitudes may be different across countries. This phenomenon may be partly due to legislative differences across countries and partly due to a different general propensity toward patenting (i.e., in some countries, firms might be more likely to patent new inventions than in others).[1]

3 Empirical settings

The IPAT model initially originated from a controversy regarding environmental degradation's driving factors between Commoner (1971) and Ehrlich and Holdren (1971), which included the three indicators of population (P), Affluence (A) and Technology (T) in the context of analysis to form the formula of. The result was a model that integrated the mutual effect that these three factors exert on environmental pollution I (Impact). Dietz and Rosa (1994) developed a stochastic framework to allow for inferences in the IPAT model. This stochastic model (STIRPAT), which is adopted in the present analysis, also allows for other influential factors to be added to analyse their influence on environmental performance.

Starting from these premises, in the present work, we estimate the following equation:

$$\mathrm{CO_2} \text{ or } \frac{\mathrm{CO_2}}{\mathrm{VA}} = \alpha_i + \tau_i + \beta_1 \,\text{population}_{it} + \beta_2 \,\text{value added}_{it} + \beta_3 \,\text{green}\, K \,\text{stock}_{it} + \varepsilon_{it} \tag{1}$$

where α_{it} and τ_{it} are, respectively, provincial and year fixed effect, and ε_{it} is the error term. The two-way fixed-effect model is estimated trough an ordinary least square estimator.[2] Dependent variables are CO_{2it} and $\mathrm{CO_2/VA}_{it}$ which, according to the IPAT/STIRPAT framework, represent environmental effects and environmental productivity respectively, for province i in year t. $\mathrm{CO_2}$ in particular, reflects the total environmental effects of economic activities, and $\mathrm{CO_2/VA}$ accounts for the size of the economy and it is a widely used indicator of environmental productivity (see, among others, Repetto 1990; Gilli et al. 2014). We believe that considering both dependent variables may provide interesting new insights to the literature,

[1] An example of study dealing with the value of patent rights can be found in Harhoff et al. (1999), while Co (2004) presents an interesting analysis on the role of patent rights in international trade. For more information on the use of patents in economic analysis see OECD (2009).

[2] We included year and provincial fixed effect to control for unobserved heterogeneity. Standard Hausman test (see Table 2 below) rejects the null hypothesis of consistency of the random effect model, motivating the choice of the fixed effect estimator. Moreover, all the dummies being jointly significant (see F test in Table 2) we prefer the fixed effects model over a pooled OLS model.

disentangling the effect that green technological change has in both relative and absolute terms.

The control variables, Population_{it} and Value Added_{it} are denoted by the terms P and A in the IPAT framework, i.e., the size of human population of the chosen economy (P) and its level of consumption (A), respectively.

Finally, $\text{Green K stock}_{\text{it}}$ and K Stock_{it} represent the indicator of green technological change and general technological change, computed using data on patent applications[3] filed at the European patent office (EPO).[4] Because EPO applications are more expensive, Italian inventors typically first file a patent application in their home country and later apply to the EPO if they desire protection in multiple European countries. As a consequence, EPO patents are generally considered to be higher-quality than the national documents and tend to be more homogeneous in value. We believe that this choice partially mitigates the difficulty in disentangling the value of different patents in the stock. The above indicators are derived according to OECD classification.[5] Table 1 summarises the variables used and presents basic descriptive statistics.

Some final caveats on the empirical strategies are important. First, the empirical analysis is based on a balanced panel dataset of 475 observations. The dataset is built by merging the data sources of all 95 Italian provinces over the years 1990–2010, each wave of data covering a 5 year period (e.g., waves were available in 1990, in 1995, in 2000, and so on). It is important to note that the country changed its administrative configuration several times during the considered period; consequently, in 2010, there were 12 more provinces than in 1990. To ensure comparability, we refer in the paper to the 1990 configuration, harmonising data when needed.[6] Second, regressions are run first on the entire Italian territory and only secondly, the sample is split into two subsamples, i.e., Northern regions and Southern regions. The Northern regions include all Northwest and Northeast regions, and the Southern area includes Central and Southern regions and Islands. The purpose of this second set of regressions is to analyse the different patterns of the effect of green patents on CO_2 emission intensity. Third, we did not include the flow of patent applications, but following Popp et al. (2011) we considered the stock of past knowledge. In fact, on the one hand, the effect of new technology on environmental performance is not instantaneous, and on the other hand, the effect of older technology is meant to

[3] An extensive discussion of the use of patents as an indicator of innovative activity is provided in Sect. 2.

[4] Applicants may choose to apply at the European Patent Office (EPO), rather than applying to individual patent offices, and designate as many of the EPO member states for protection as desired. The application is examined by the EPO. If granted, the patent is transferred to the individual national patent offices designated for protection. Since 1997, the designation of any additional member states is free after the first seven. Since 2004, all EPO states are automatically designated.

[5] See, for reference, OECD (2011) and other works by the OECD environmental directorate.

[6] In all instances, new provinces are the result of the division in two new administrative entities of an old province. For this reason, we always reconstructed the 1990 data merging the new provinces into the old one.

Table 1 Descriptive statistics. Data available for years 1990–1995–2000–2005–2010

Acronym	Description	Obs	Mean	SD	Min	Max	Source
CO_2	Provincial CO_2 emissions	475	6153986	1.50e + 07	273827.9	1.56e + 08	ISTAT
CO_2/VA	Provincial environmental performance (provincial CO_2 divided by provincial value added)	475	402.4777	909.0944	15.31121	12453.51	
Population	Number of inhabitants	475	662751.3	717902.4	88789	5616384	ISTAT
Value added	Provincial value added per capita (€2000)	475	16885.65	6898.745	4126.183	34211.29	ISTAT
Total patent	Total patent application by priority year	475	22.80369	73.91732	0	1025.178	OECD
Green patent	Total green patent application by priority year	475	0.4678992	1.567439	0	32	OECD
K stock	Total patent stock according to Popp (2002, 2011)	475	153.3781	475.7808	0	5906.982	OECD
Green K stock	Total green patent stock according to Popp (2002, 2011)	475	3.124856	8.321245	0	102.1265	OECD

decrease over time. Therefore, we need to discount the number of both total and green patents according to the following formula:

$$K\ \text{Stock}_{i,t} = \sum_{s=0}^{\infty} e^{-\beta 1(s)}\left(1 - e^{-\beta 2(s+1)}\right)\text{PAT}_{i,j,t-s} \qquad (2)$$

According to the previous literature (Popp 2002), the rate of knowledge obsolescence is set equal to 0.1 (β1 = 0.1) and the rate of knowledge diffusion to 0.25 (β2 = 0.25). The resulting knowledge stock varies by province and technology. According to Popp et al. (2011), year fixed effects have been included in all specifications to account for the tendency of knowledge stock to grow over time.

4 Results

Table 2 below presents regression results obtained from the estimation of the model in Eq. 2, using two different dependent variables (CO_2 and CO_2/VA, respectively) and applying five different specifications. In Specification I, in particular, we use the Green Knowledge Stock to account for technological change dynamics, whereas in Specification II, we employ the stock of total knowledge to test for the effect of overall patenting on our dependent variable. This approach enriches the first specification and provide complementary results. If the effect of green technologies

Table 2 Estimation results

Specification	I		II		III		IV		V	
Dependent variable	CO_2	CO_2/VA	CO_2	CO_2/VA	CO_2	CO_2/VA	CO_2	CO_2/VA	CO_2	CO_2/VA
Green K stock	10477.79	−42.80***			11741.06	−42.02***	−113388.56	−207.47***	−3656931*	−285.68***
	(26872.89)	(5.06)			(31134.51)	(5.41)	(309637.26)	(75.26)	1885001	(115.16)
Population	0.05	−0.00	−0.04	−0.00	−0.09	−0.00	0.35	−0.00	0.01	0.01
	(0.71)	(0.00)	(0.72)	(0.00)	(0.97)	(0.00)	(0.91)	(0.00)	(0.01)	(0.01)
Value added	−55.93	0.02**	−31.10	0.02	−180.52	−0.02	−228.88	−0.00	−625.17**	−0.0367
	(63.53)	(0.01)	(63.75)	(0.01)	(125.31)	(0.02)	(153.32)	(0.04)	(260.28)	(0.016)
K stock			−322.77	−0.64***						
			(506.78)	(0.10)						
K stock × North dummy									3806181	290.22***
									(2276351)	(112.45)
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	North	North	South	South	Full	Full
Hausman test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
F test on provincial dummies	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
N	475	475	475	475	305	305	170	170	475	475

*, **, *** Indicate significance at 10, 5 and 1 % levels, respectively. OLS estimates. All regressions include year and country effects. The *F* test on provincial dummies tests the null hypothesis of all dummies being jointly equal to zero. In specification V, a North/South Dummy is included

on climate change mitigation is expected to be positive, we do not have a priori expectations of the total knowledge stock. Several countervailing forces play a role in this case: from the one hand an increase in total knowledge can be environmentally exacerbating, given that it could be connected with an intensified economic activity and thus an increase in CO_2 emission, while on the other hand it can also be beneficial for the environment if the adoption knowledge is driven by the search for new processes/technologies which are good for the environment. Specification III restricts the sample to only Northern provinces to determine whether the results are driven by geographical disparities, whereas Specification IV studies the behaviour of Southern provinces only. Given the significant correlations among variables (see Fig. 5 and Table 3 in the appendix) a VIF is computed after each regression, in order to detect severe multicollinearity. However, the indicator do not highlight that collinearity as an issue in this analysis. Finally in Specification V we propose an alternative way to estimate the difference in the effect of the green knowledge stock in the two samples by interacting the stock variable with a dummy equal to one for northern regions.

Specification I results show that technological change only exerts an effect on environmental productivity and that any effects is found with respect to CO_2. In particular, column 2 shows a statistically significant and negative coefficient of Green K Stock, which confirms the hypothesis that an increase in a country's green knowledge base, measured here by green patent stock, has a positive effect on environmental productivity. However, there is no evidence of a positive technological effect with respect to total CO_2 emissions. Regarding the other covariates, population is not statistically significant in the Italian context, which is a reasonable result in an industrialised country like Italy, characterised by slowly changing demographic trends.[7] On the contrary, VA shows a significant and positive coefficient in column 2 but not in column 1. This latter result confirms the evidence found in previous EKC studies, which found no absolute delinking between CO_2 or CO_2/VA and economic indicators (Marin and Mazzanti 2010). Referring to the EKC context, Column 2 shows the presence of a monotonically increasing relationship (also known as relative delinking) between economic growth and CO_2/VA. Overall, these results suggest that, roughly speaking, although green technological change has a positive effect on environmental productivity, it has not been able to shrink the total level of emission. From a macro perspective, a negative scale effect (partially confirmed by the significance of value added) seems to prevail on the positive technological effect. Regarding the quantification of results, a one standard deviation increase in the stock of green knowledge leads to a 0.39 standard deviation decrease in CO_2/VA, and an increase of the same size in value added increases environmental productivity by a standard deviation of approximately 0.19.

The regression results of Specification II basically confirms previous evidence, and the magnitude of the coefficient is fairly similar (the standardised coefficient of knowledge stock is equal to −0.34). This phenomenon also suggests that employing

[7] The average population across Italian provinces was 597,663 in 1990 and 633,791 in 2010, showing only a limited increase in population in the two decades. Moreover, we note that the within variation of population in the panel is five times lower than the between variation, suggesting that the time dimension, in this case, is not relevant.

a broader concept of technical change does not alter previous evidence. This is not an obvious result, considering that total knowledge stock also includes brown patents, which might have a negative effect on emissions if they increase the value added of pollution-intense sectors. (See Aghion et al. 2012, for a discussion of brown and green patents and their effect on the environment.)

Specifications III and IV show that the aggregate results also hold when splitting the full data set into the two subsamples of Northern and Southern regions of Italy. In this case, the primary evidence does not change, but the magnitude of the effects is much stronger in the South, where 1 standard deviation increase in the green knowledge stock leads to an increase in the dependent variable equal to 1.9 standard deviations, whereas the effect in the North is very similar to the national average.[8] This latter result—particularly if compared to the descriptive statistics of Figs. 1, 2, 3 and 4, which highlighted how the South tends to have a lower patent propensity—suggests that in these areas, even a small marginal increase in knowledge formation can have a strong effect on environmental productivity. Finally, the main evidence also holds in Specification V, where we interacted the Green K Stock with a north dummy. Interestingly the result confirms that the effect is much stronger for southern regions.

5 Conclusions

This paper has carefully examined primary main factors that may influence CO_2 emissions according to the IPAT/STIRPAT framework exploiting an original dataset that covers 95 Italian provinces over the years 1990–2010.

The primary evidence shows that the stock of green patents did not exert a significant effect on CO_2 reduction in Italy; instead, it improved overall environmental productivity. On the contrary, the growth in the scale of the economy, proxied here by Value Added, slowed environmental productivity by exerting more pressure on the environment. Overall, this evidence suggests that technology has not yet played a significant role in promoting environmental protection, although a scale effect seems to prevail. Notably, however, green technological change is positively correlated with environmental productivity, and this correlation is stronger in the South, which suggests that some technological effects are emerging in the country.

Acknowledgments The authors acknowledge financial support of the Italian National Research Project PRIN-MIUR 2010-11 “Climate changes in the Mediterranean area: scenarios, mitigation policies and technological innovation” (2010S2LHSE_002). Usual disclaimers apply.

Appendix

See Table 3 and Fig. 5.

[8] An F test, not included for sake of brevity, rejects the null hypothesis that the two coefficients are significant across the two samples.

Table 3 Correlation matrix of the dependent and explanatory variables

	CO_2	CO_2/VA	Pop	VA	Green K stock	K stock
CO_2	1					
CO_2/VA	0.8941	1				
Pop	0.4752	0.4223	1			
VA	0.1038	−0.1026	0.0976	1		
Green K stock	0.4728	0.2927	0.6798	0.4130	1	
K stock	0.4453	0.2867	0.6214	0.3761	0.9598	1

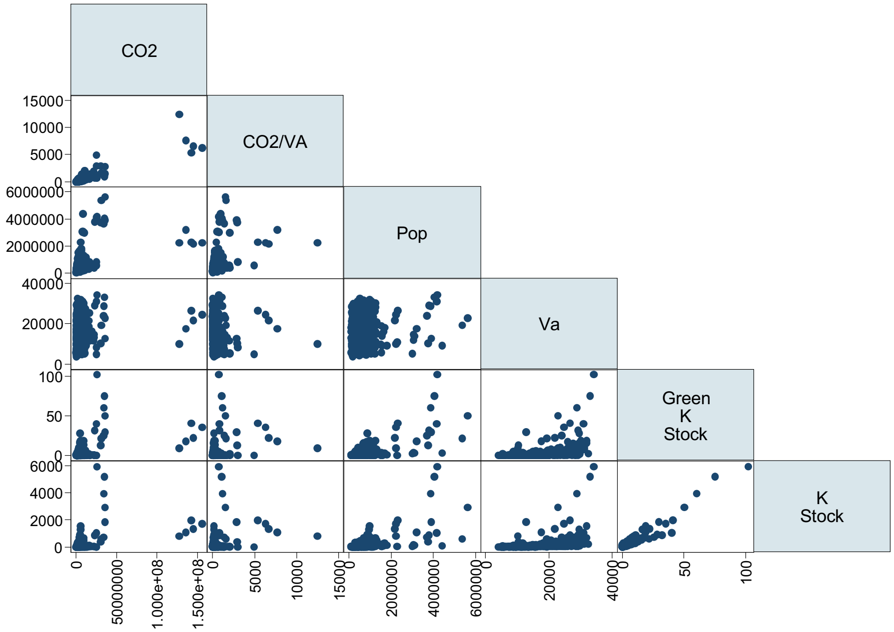

Fig. 5 Scatterplot matrix of the dependent and explanatory variables

References

Abbott FM (2012) Innovation and technology transfer to address climate change: lessons from the global debate on intellectual property and public health. International Centre for Trade and Sustainable Development, Issue Paper no. 24

Aghion P, Dechezleprêtre A, Hemous D, Martin R, Van Reenen J (2012) Carbon taxes path dependency and directed technical change: evidence from the auto industry. NBER working paper no. 18596

Anton WRQ, Deltas G, Khanna M (2004) Incentives for environmental self-regulation and implications for environmental performance. J Environ Econ Manag 48:632–654

Berrone P, Fosfuri A, Gelabert R, Gomez-Mejia LR (2013) Necessity as the mother of "green" inventions: institutional pressures and environmental innovations. Strateg Manag J 34:891–909

Borhan H, Ahmed EM, Hitam M (2012) The impact of CO_2 on economic growth in Asean 8. Procedia Soc Behav Sci 35:389–397

Brizga J, Feng K, Hubacek K (2013) Drivers of CO_2 emissions in the former Soviet Union: a country level IPAT analysis from 1990 to 2010. Energy 59:743–753

Cai WG, Zhou XL (2014) On the drivers of eco-innovation: empirical evidence from China. J Clean Prod 79:239–248

Carrión-Flores CE, Innes R (2010) Environmental innovation and environmental performance. J Environ Econ Manag 59(1):27–42

Carson RT (2010) The environmental Kuznets curve: seeking empirical regularity and theoretical structure. Rev Environ Econ Policy 4(1):3–23

Cecere G, Corrocher N, Gossart C, Ozman M (2014) Lock-in and path dependence: an evolutionary a: roach to eco-innovations. J Evol Econ 24(5):1037–1065

Chong WHB, Guan D, Guthrie P (2012) Comparative analysis of carbonization drivers in China's megacities. J Ind Ecol 16:564–575

Christmann P (2000) Effects of "best practices" of environmental management on cost advantage: the role of complementary assets. Acad Manage J 43:663–680

Co CY (2004) Do patent rights regimes matter? Rev Int Econ 12(3):359–373

Cole MA, Neumayer E (2004) Examining the impact of demographic factors on air pollution. Popul Environ 26:5–21

Commoner B (1971) The closing circle: nature man and technology. In: Cahn MA, Brien RO, Sharpe ME (eds) Thinking about the environment: readings on politics property and the physical world. Armonk, New York, pp 167–186

Costantini V, Mazzanti M, Montini A (2013) Environmental performance innovation and spillovers Evidence from a regional NAMEA. Ecol Econ 89:101–114

De Haan M (2004) Accounting for goods and bads: measuring environmental pressure in a national accounts framework. Ph.D. Dissertation. Universiteit Twente, Enschede

Del Río P (2009) The empirical analysis of the determinants for environmental technological change: a research agenda. Ecol Econ 68(3):861–878

Del Río P, Tarancón Morán MÁ, Albiñana FC (2011) Analysing the determinants of environmental technology investments. A panel-data study of Spanish industrial sectors. J Clean Prod 19:1170–1179

Dernis H, Kahn M (2004) Triadic patent families methodology. OECD science, technology and industry working papers, no. 2004/02 OECD Publishing

Dietz T, Rosa EA (1994) Rethinking the environmental impacts of population, affluence and technology. Hum Ecol Rev 1(2):277–300

Dietz T, Rosa EA (1997) Effects of population and affluence on CO_2 emissions. Proc Natl Acad Sci USA 94:175–179

Dopfer K (2012) The origins of meso economics. J Evol Econ 22:133–160

Ehrlich P, Holdren J (1971) Impact of population growth. Science 171:1212–1217

Fan Y, Liu LC, Wu G, Wei YM (2006) Analyzing impact factors of CO_2 emissions using the STIRPAT model. Environ Impact Asses 26:377–395

Feng K, Siu YL, Guan D (2012) Analyzing drivers of regional carbon dioxide emissions for China: a structural decomposition analysis. J Ind Ecol 16:600–611

Gilli M, Mancinelli S, Mazzanti M (2014) Innovation complementarity and environmental productivity effects: reality or delusion? Evidence from the EU. Ecol Econ 103:56–67

Goulder LH, Schneider SH (1999) Induced technological change and the attractiveness of CO_2 abatement policies. Resour Energy Econ 21(3–4):211–253

Griliches Z (1990) Patent statistics as economic indicators. NBER working paper no. 3301

Grossman GM, Krueger AB (1995) Economic growth and the environment. Q J Econ 110:353–377

Harhoff D, Narin F, Scherer FM, Vopel K (1999) Citation frequency and the value of patented inventions. Rev Econ Stat 81(3):511–515

Kaya Y (1990) Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. Paper presented to the IPCC Energy and Industry Subgroup, Response Strategies Working Group, Paris (mimeo)

Kerr D, Mellon H (2012) Population and the environment: exploring Canada's record on CO_2 emissions and energy use relative to other OECD countries. Popul Environ 34:257–278

Kim K, Kim Y (2012) International comparison of industrial CO_2 emission trends and the energy efficiency paradox utilizing production-based decomposition. Energy Econ 34(5):1724–1741

Kwon TH (2005) Decomposition of factors determining the trend of CO_2 emissions from car travel in Great Britain (1970–2000). Ecol Econ 53:261–275

Liddle B (2004) Demographic dynamics and per capita environmental impact: using panel regressions and household decompositions to examine population and transport. Popul Environ 26:23–39
Liddle B, Lung S (2010) Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. Popul Environ 31(5):317–343
Liu Z, Liang S, Geng Y, Xue B, Xi F, Pan Y, Zhang T, Fujita T (2012) Features trajectories and driving forces for energy-related GHG emissions from Chinese mega cites: the case of Beijing Tianjin Shanghai and Chongqing. Energy 37:245–254
MacKellar LF, Lutz W, Prinz C, Goujon A (1995) Population, households, and CO_2 emissions. Popul Dev Rev 21(4):849–865
Marin G, Mazzanti M (2010) The evolution of environmental and labor productivity dynamics. J Evol Econ 23(2):357–399
Mazzanti M, Montini A (2010) Embedding the drivers of emission efficiency at regional level—analyses of NAMEA data. Ecol Econ 69:2457–2467
O'Neill BC, Chen BS (2002) Demographic determinants of household energy use in the United States. Popul Dev Rev 28:53–88
OECD (2009) OECD Patent statistics manual. OECD Publishing, Paris
OECD (2011) Invention and transfer of environmental technologies. OECD Publishing, Paris
Popp D (2002) Induced innovation and energy prices. Am Econ Rev 92:160–180
Popp D, Hascic I, Medhi N (2011) Technology and the diffusion of renewable energy. Energy Econ 33(4):648–662
Prskawetz A, Leiwen J, O'Neill B (2004) Demographic composition and projections of car use in Austria. Vienna Yearbook Popul Res 175–201
Repetto R (1990) Environmental productivity and why it is so important. Chall 33(5):33–38
Shi A (2003) The impact of population pressure on global carbon dioxide emissions 1975–1996: evidence from pooled cross-country data. Ecol Econ 44:29–42
Wang Z, Yang Z, Zhang Y, Yin J (2012) Energy technology patents—CO_2 emissions nexus: an empirical analysis from China. Energ Policy 42:248–260
York R, Rosa EA, Dietz T (2003) STIRPAT IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol Econ 46:351–365
Zagheni E (2011) The leverage of demographic dynamics on carbon dioxide emissions: does age structure matter? Demography 48:371–399