Green inventions and greenhouse gas emission dynamics

A close examination of provincial Italian data

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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 and both CO_2 emissions and emission efficiency (CO_2/VA), exploiting a rich panel covering 95 Italian provinces from 1990-2010. The main regression results suggest that green technology has not yet played a significant role in promoting environmental protection, although it significantly 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

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1 Introduction

Carbon dioxide emissions and the improvement of environmental efficiency in relation to global warming have become urgent issuesthroughout the world. Over the last two decades, economic growth has been associated with a 44% increase in CO_2 levels, and only a small number of countries have managed to decrease their emissions during this period.[1]

The advancements in science and technology are considered to be key concerns in addressing environmental issues and confronting climate change (Abbott, 2009; Thomas, 2008), 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. For example, Pascual Berrone and Andrea Fosfuri (2013) conducted research from a firm-level viewpoint and discussed the reason why some firms engage in more environmental innovation than others, considering the interaction of both institutional pressures and factors internal to the firm's organisation. Similarly, Wu-gan Cai and Xiao-liang Zhou (2014) conducted an empirical test to determine the primary factors that influence the adoption of eco-innovation in Chinese firms. Findings in both of these works suggest that eco-innovation is triggered by a complex and firm specific mixture of internal and external drivers.

Another branch of the environmental innovation literaturehas focused on a sector-level perspective. Goulder and Schneider (1999) studied the effect of R&D activities on carbon dioxide emission reduction policies and concluded that R&D could actually lower the GDP costs of carbon dioxide emissions. Pablo del Rio et al. (2011), who investigated the drivers of environmental innovation on a panel of Spanish industries, 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 from Carmen E. Carrion-Flòres and Robert Innes (2010) reveal 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. Valeria Costantini and Massimiliano Mazzanti (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.

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[1] CO_2 emissions by product and flow. IEA CO2 emissions from fuel combustion statistics (database). IEA; 2012

From a country perspective, many authors highlighted differences in pollution emissions trends across countries or group of countries. For example, Kyunam Kim and Yeonbae Kim (2012) studied the CO2 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 technical 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.

The preliminary evidence (at the regional level) presented in Figures 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 two 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 (Figure 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. Finally, Figure 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 regions such as Lombardia, Piemonte, Veneto and Emilia-Romagna.

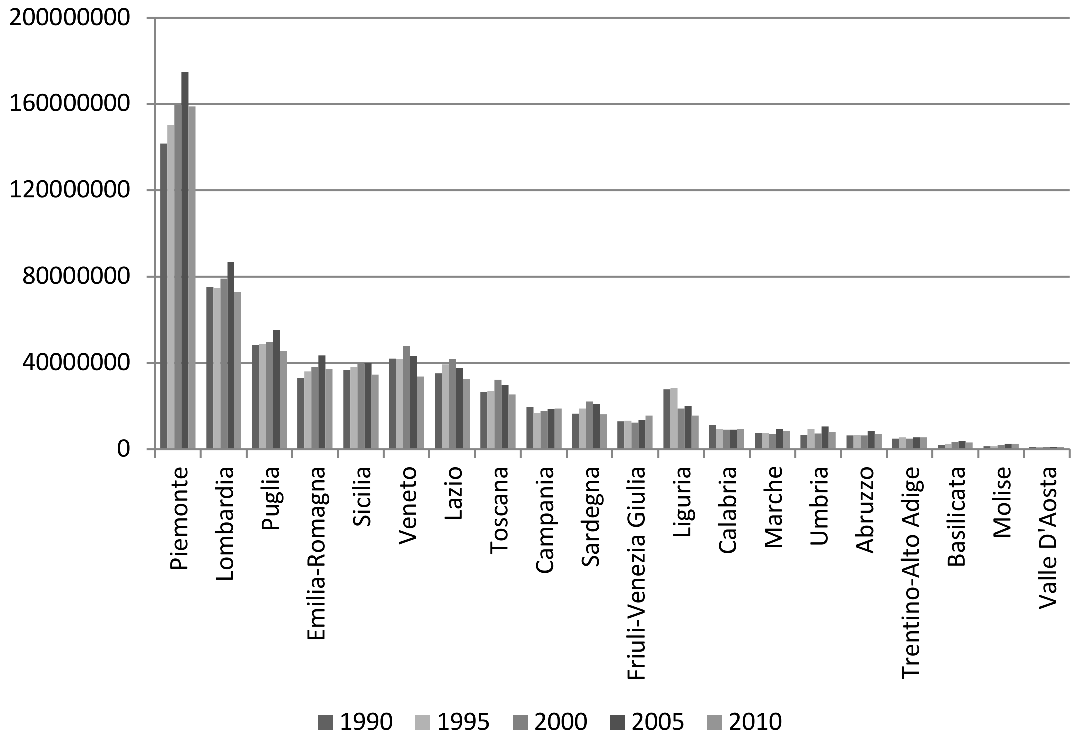

Figure 1. The CO_2 emission of 20 Regions in Italy for 5 selected years (Unit: Mg)

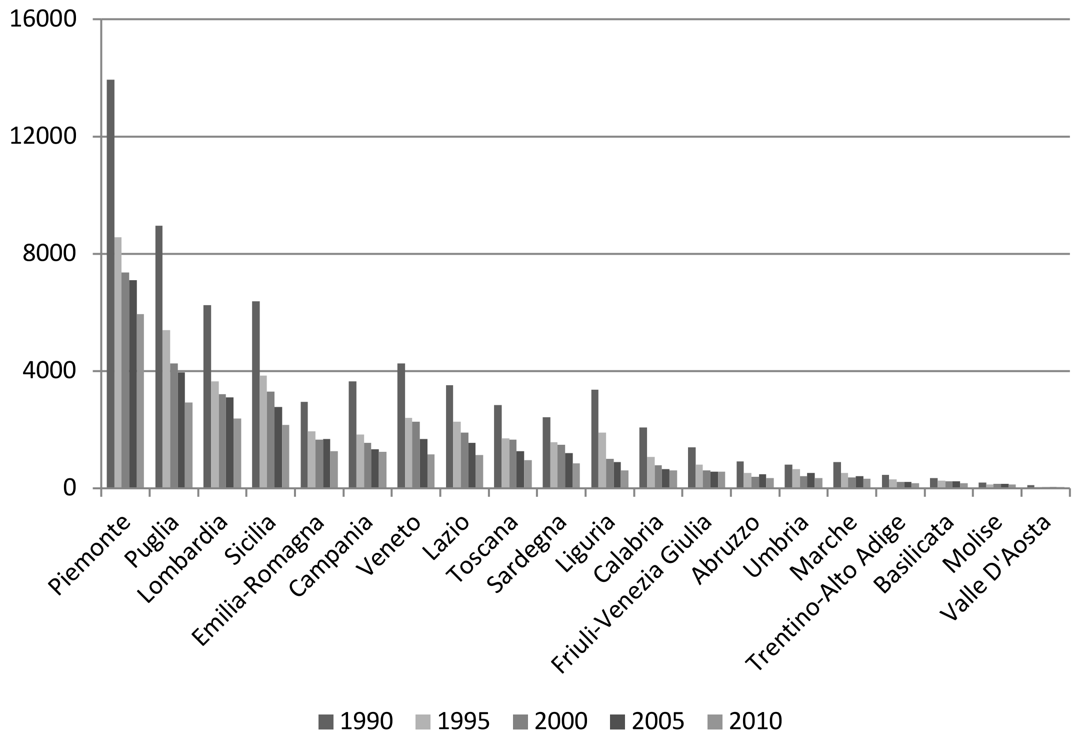

Figure 2. Emission Intensity (CO_2/VA) across of 20 Regions in Italy for 5 selected years (Unit: Mg/VA)

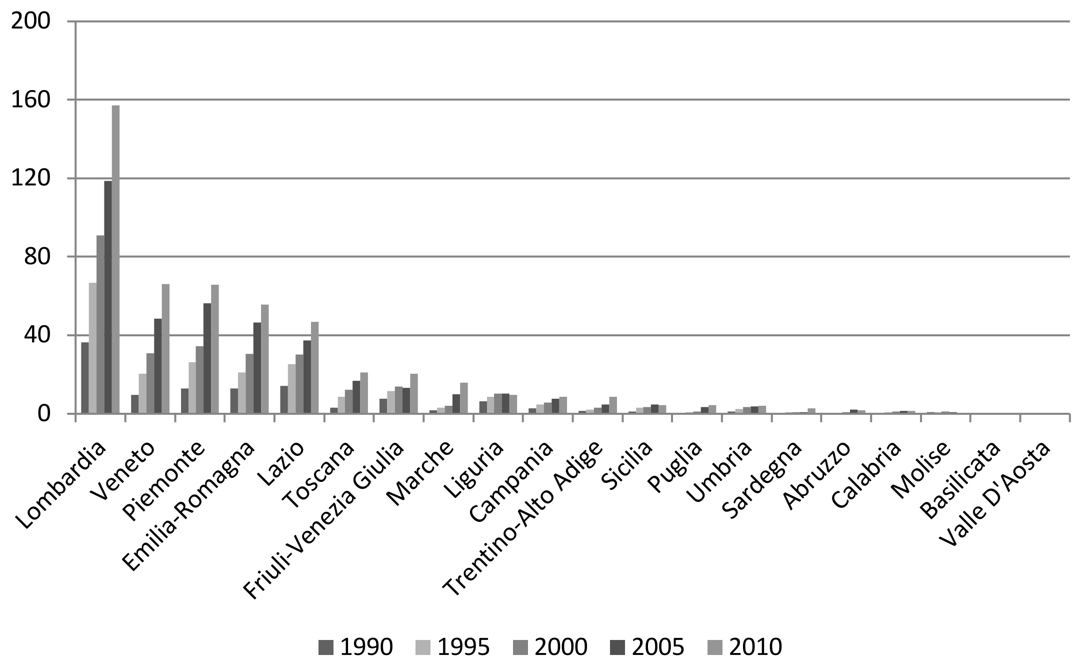

Figure 3. Green Patent Stock for 20 Italian regions in the 5 selected years.

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 (NAMEA; Mazzanti et al., 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 five 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 CO2 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: section 2 presents emissions' main driving forces; section 3 describes the empirical approach; section 4 discusses the main results; and section 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 analysis have applied the IPAT framework to build a model for polluting emissions (e.g.: Dietz et al., 2009; 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; Wang and Huang, 2008; Xu et al., 2006).

The following paragraphs will explain some of these 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). Thomas Dietz (1997) and Richard York (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; Liddle, 2011).

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 GHG (greenhouse gas) 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. Ying 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.

2.3 Technology

Green technology is meant to play a central role in reducing the environmental effect of CO2 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 CO2 emission in China, found that innovations that are oriented toward carbon-free technologies can significantly help lower CO2 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, Deltas, and Khanna, 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).

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 $I = P \cdot A \cdot T$. The result was a model that integrated the mutual effect that these three factors exert on environmental pollution I (Impact). Thomas Dietz et al. (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:

$$CO_2 \ or \ \frac{CO_2}{VA} = \alpha_{it} + \tau_{it} + \beta_1 Population_{it} + \beta_2 Value\ Added_{it} + \beta_3 Green\ K\ Stock_{it} + \varepsilon_{it}$$

where α_{it} and τ_{it} are, respectively, provincial and year fixed effect, and ε_{it} is the error term. Dependent variables are $CO2_{it}$ and $CO2/VA_{it}$ which, according to the IPAT/STIRPAT framework, represent environmental effects and environmental productivity, respectively, for province *i* in year *t*. CO_2 in particular, reflects the total environmental effects of economic activities, and CO_2/VA accounts for the size of the economy and 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, disentangling the effect that green technological change has both in 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, $Green\ K\ Stock_{it}$ and $K\ Stock_{it}$ represent the indicator of green technological change and general technological change, computed using data on patent applications[2] filed at the European patent office (EPO)[3]. 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[4]. Table 1 summarises the variables used and presents basic descriptive statistics.

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2 An extensive discussion of the use of patents as an indicator of innovative activity is provided in section 2.

3 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.

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

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, with 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 safeguard comparability, we refer in the paper to the 1990 configuration, harmonising data when needed[5]. Second, regressions are run first on the entire Italian territory, and second, 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, in the empirical analysis, 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 decrease over time. Therefore, we need to discount the number of both total and green patents according to the following formula (Popp, 2002):

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

According to the previous literature, the rate of knowledge obsolescence is set equal to 0.1 ($\beta1=0.1$) and the rate of knowledge diffusion to 0.25 ($\beta\ 2=0.25$). The resulting knowledge stock varies by province and technology. In accordance with 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.

[5]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.

Acronim	**Description**	**Obs**	**Mean**	**St. Dev.**	**Min**	**Max**	**Source**
CO_2	Provincial CO2 emissions.	475	6153986	1.50e+07	273827.9	1.56e+08	ISTAT
CO_2/VA	Environmental performance (CO2 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	.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

4. Results

Table 2 below presents regression results obtained from the estimation of the model in equation 2, using two different dependent variables (CO_2 and CO_2/VA, respectively) and applying four different specifications. In Specification I, in particular, we use the Green Knowledge Stock to account for technological change dynamics, whereas in Specification II, we control for the robustness of this measure employing the stock of total knowledge. 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.

Specification I results show that technological change only exerts an effect on environmental productivity and that no correlation is found with respect to total environmental effects. 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 emission. 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[1]. On the contrary, VA shows a significant and positive coefficient in column 2 and no significance 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, 2013). Referring to the EKC context, Column 2 shows only 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 Green K Stock led to a 0.39 standard deviation decrease in CO_2/VA, and an increase of the same size in value added increased the dependent variable by a standard deviation of approximately 0.19.

The regression results of Specification II basically confirm 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 a broader concept of technical change does not alter previous evidence. This is a 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.)

Finally, 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 K Stock leads to an

[1]The average population across Italian provinces was 597663 in 1990 and 633791 in 2010, showing no significant increase.

increase in the dependent variable equal to 1.9 standard deviations, whereas the effect in the North is very similar to the national average. This latter result—particularly if compared to the descriptive statistics of Figures 1-4, 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.

Table 2. Estimation results

Specification	**I**		**II**		**III**		**IV**	
Dependent Variable	*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***
	(26872.89)	(5.06)			(31134.51)	(5.41)	(309637.26)	(75.26)
Population	0.05	-0.00	-0.04	-0.00	-0.09	-0.00	0.35	-0.00
	(0.71)	(0.00)	(0.72)	(0.00)	(0.97)	(0.00)	(0.91)	(0.00)
Value Added	-55.93	0.02**	-31.10	0.02	-180.52	-0.02	-228.88	-0.00
	(63.53)	(0.01)	(63.75)	(0.01)	(125.31)	(0.02)	(153.32)	(0.04)
K Stock			-322.77	-0.64***				
			(506.78)	(0.10)				
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	North	North	South	South
N	475	475	475	475	305	305	170	170

*, **, *** indicate significance at 10%, 5% and 1% levels, respectively. All regressions include year and country effects.

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 CO2 reduction; 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.

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