Environmental Performance, Innovation and spillovers. Evidence from a Regional NAMEA

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Analysis

Environmental performance, innovation and spillovers. Evidence from a regional NAMEA

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A B S T R A C T

The achievement of positive Environmental Performance (EP) at national level could strongly depend on differences in regional features, namely productive specialization, regulation stringency and innovation capabilities of both public institutions and the private business sector. We present empirical evidence for a newly released NAMEA available for the 20 Italian regions in order to demonstrate the role played by sector innovation, regional spillovers and environmental policies. The Italian North–south divide regarding industrial development and productive specialization patterns seems to affect regional EP. Nonetheless, such a pattern presents some interesting differences, revealing a more heterogeneous distribution of emissions which may reflect the role of other driving forces. In particular, agglomerative effects seem to play a major role and the EP of neighboring regions influences the regional internal EP. This means that together with the spatial concentration of specific sectors into restricted areas, there is also some convergence in the adoption of cleaner or dirtier production process techniques. Finally, interregional technological spillovers are more important than sector internal innovation for improving EP, revealing that accounting for spatial features and linking ecological economics to regional economics are crucial in understanding the key drivers of EP.

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1. Introduction

This paper investigates the economic drivers that may influence the geographical distribution of sectoral environmental performance (EP hereafter) by using a new and innovative hybrid environmental-economic accounting matrix applied to the Italian regions, based on the NAMEA (National Accounting Matrix including Environmental Accounts) approach. As background information, the first NAMEA was developed by the Dutch Central Bureau of Statistics (De Boo et al., 1993) and earlier contributions such as Ike (1999), Keuning et al. (1999), Steenge (1999), and Vaze (1999) provided empirical analyses related to the possible policy implications deriving from sector-specific EP analyses. In the NAMEA tables, air emissions and economic data (value added, final consumption expenditures and full-time equivalent job) are assigned to the economic branches or resident units directly responsible for environmental and economic phenomena. According to Tudini and Vetrella (2012), current NAMEA Italian tables at national level cover 51 distinguished sectors (manufacturing and services in the NACE classification) and households (where emission levels are distinguished for final use, as transport, heating and other). Main pollutant emissions are carbon dioxide (CO₂), nitrous oxide (N₂O), methane (CH₄), oxides of nitrogen (NOₓ), sulfur oxides (SOₓ), ammonia (NH₃), non-methane volatile organic compounds (NMVOCs), carbon monoxide (CO), and particulate matter (PM₁₀). For both production activities and households, environmental pressures are allocated to who is directly responsible for their generation (due to production or consumption processes respectively for industries and households).

It is worth noting that EUROSTAT released the first full EU27 NAMEA in 2011 (Eurostat, 2011). This effort is considered a silver bullet in EU strategy on environmental data generation for policy support, since it is recognized as a powerful instrument for assessing sustainable production and consumption performance (Watson and Moll, 2008).

The regionalization of the NAMEA data is a relatively new framework. The big advantage is that it adds a geographical dimension to
the already existing sectoral one, allowing the structural and efficiency factors behind the geography of EP to be disentangled.

The relationships between economic and environmental performances have been increasingly studied over the past years by sector based analyses that have roots in Input Output (I–O) and NAMEA frameworks. Hybrid environmental and economic accounts have also benefited from recent efforts in the extended environmental input output (EEIO) approach. As described in Tukker et al. (2006), EEIO approach allows identifying the main sources of environmental problems within the economic system, thus providing information for ex-ante impact assessment of environmental protection policies, as well as informing policy-making at the strategic level about trends in the environmental performance of the economy and their drivers. The adoption of an EEIO approach has been also motivated by the interest in investigating the role of trade and technology diffusion in international relationships when EP is under scrutiny (Costantini et al., 2012; Marin et al., 2012; Moll et al., 2007).

While several efforts in producing better and more precise EP analytical tools based on hybrid accounts are well established (De Haan, 2004; De Haan and Reuning, 1996; Mazzanti et al., 2008; Mazzanti and Montini, 2010a), analysis based on the sub national/regional level is much less investigated. Its value is at least twofold: (i) increasing attention is now devoted by policy makers at EU level to regional development and regional specialization strategies; (ii) there is recognition that sustainable performance at country level depends also on how regions interact and correlate to each other in their achievement of policy goals (CE, 2009). The interest for ecological economics scholars might be that regional economic development and environmental performance may be part of a virtuous circle, or conversely that pollution hot spots depend on regional specialization as well as on geographical spillovers.

In this paper, we examine these factors by placing a special emphasis on the role of geographical spillovers and sectoral technological regimes with the aid of region/sector based hybrid economic and environmental accounting data (Hoekstra and van den Bergh, 2006; Huppes et al., 2005).

In the seminal works by Malerba (2006) and Malerba and Orsenigo (2000), the paradigm of technological regimes is the key concept for studying the different ways in which innovative activities are organized and, more relevant for us, their main finding is that innovative activities are sector specific, insofar as the features of technological environments are common to groups of industries, while they are invariant with respect to the institutional context. Recent analyses in regional economics have also emphasized the crucial role of geographical spillovers in shaping development paths of localized areas, especially related to knowledge flows at regional level (Boschma and Iammarino, 2009; Bottazzi and Peri, 2003).

Hence, we intend to examine if the agglomeration effects, found in various studies as an explanation for heterogeneous economic performance (Brioschi et al., 2002; Cainelli et al., 2006, 2007, 2012; Cefis et al., 2009), also explain the geography of EP.

The main original contribution of this paper is to explore how EP is distributed among regions and sectors and to try to discover if some agglomerative effects occur and if their impact corresponds to a regional and sectoral criterion. From a policy perspective, the regional lens is a necessary complement to the international view since the overall capacity of a country to be compliant with environmental protection purposes depends on how its internal specialization is distributed among local areas and how local areas dialog between themselves. This is a typical political economy problem, where subsidiarization and federalism principles applied to policy decisions at sub-national level may bring to second best solutions due to free riding behaviors from those local areas with smaller convenience in investing in environmental protection activities (Fiorillo and Sacchi, 2011a,b).

Research questions of our study are thus summarized as: (i) we analyze if internal sector/region specific technological regimes are relevant in explaining EP; (ii) we also investigate if there are agglomerative effects in terms of region/sector spillovers related to environmental and technological performances of nearby regions; (iii) if so, we try to understand if such external driving forces are predominant in shaping the regional EP with respect to internal factors. We are aware that the spatial dis-aggregation we here may consider – Italian regional level – could be not sufficiently refined for supporting a coherent environmental analysis, especially in a really socially divided and economically polarized country like Italy, where in ‘environmental federalism’ is a real hot issue (Mazzanti and Zoboli, in press). The environmental variables presented by NAMEA may in fact present a high degree of heterogeneity within each region: this accounting system could end up with being to some extent imprecise in estimating ‘environmental efficiency’. Nonetheless, it represents the only available informative tool at regional level in Italy – which shows the only full regional NAMEA at the moment – and in the EU.

There exists a case study on a single Italian region, Latium, with sub-regional data, but no comparison with other regions is really possible. Our spillovers and externalities related research hypotheses benefit from an application that refers to the entire Italian territory with regional disaggregation. In fact, particularly, in the case of manufacturing, economic activities (e.g. districts, industrial agglomerations, Cainelli, 2008; Cainelli et al., 2006) are often geographically distributed among different administrative Regions. If we narrowed down the analysis to only one single Region, Latium, this would not help in discovering generalizable phenomena, but only a small scale effect in a restricted more idiosyncratic area.

The rest of the paper is structured as follows. Section 2 presents the specification of the econometric model for representing sectoral/regional emission intensities. Section 3 presents the dataset and how we specify innovation and environmental spillovers. Section 4 presents descriptive geographical empirical findings and the results from the econometric estimations about the sectoral/regional environmental efficiency drivers. Section 5 concludes.

2. Modeling Environmental Performance and Spillovers Effects

When EP is under scrutiny, the most widely used research frameworks, addressing for different driving forces linking economic features with environmental issues, are the so-called environmental Kuznets curve (EKC) and the Impact- Population-Affluence-Technology (IPAT) realms (Andreoni and Levinson, 2001; York et al., 2003). It is worth noting that many different drivers are scrutinized under these framework, as the scale, composition and technological effects (Grossman and Krueger, 1995), the role of trade relationships (Cole, 2004), institutional quality (Dasgupta et al., 2006), and technological capabilities (Costantini and Martini, 2010). It is also worth mentioning that all these factors may have different effects in terms of EP, meaning that the empirical analysis requires a flexible enough modeling approach to account for such heterogeneous impacts. In our work we will focus on two drivers, the composition and technological effects. The composition effect relies on structural changes in economic systems, namely, shifts from a heavy manufactured system to a service-oriented economy. The technological effect argues that economic sectors may adopt less polluting technologies, either because of market-driven technological progress or government regulation, as emphasized by Cole et al. (2005).

Let us consider environmental pressure expressed here through pollutant emissions for each k-th sector in each r-th region (Ek) as a function of the production level (Yk), technology (Tk), other structural specific features (Ak) not directly related to the production function, and environmental policy (Polk) as suggested by Cole et al. (2005). Emissions are thus expressed as the following general function:

$$E_k = f(A_k, Y_k, T_k, Pol_k).$$

(1)
It is worth mentioning that all factors which may influence environmental performance have different linkages with economic development or growth patterns. This means that the empirical analysis should be based on a theoretical approach which allows polluting emissions to be not necessarily a constant proportion of income growth. This is the main reason why it is important to work on an estimable relationship that is flexible enough to permit this. To this purpose, adapting the modeling approach developed by Medlock and Soligo (2001) for the relationship between energy intensity and economic growth, emission level may be expressed as a non-constant income elasticity function in the form of:

\[ E_k^l = A_k Y_k^{(h_1 + h_2)} \theta_1 \phi_0 \theta^\Lambda \]

(2)

and the logarithmic transformation of Eq. (2) takes the form of:

\[ \ln E_k^l = \ln A_k + \alpha \ln Y_k + \gamma (\ln Y_k)^2 + \phi \ln T_k + \lambda \ln Po_k + \epsilon_k \]

(3)

where \( \epsilon_k \) is the error term.

Since we are interested in an evaluation of the EP of each sector expressed as a measure of emission intensity, we transform Eq. (3) by scaling it with region/sector specific production level, thus obtaining the following reduced form:

\[ e_k^l = \delta + \alpha_k + \beta_1 Y_k + \beta_2 \lambda Y_k + \beta_3 Po_k + \epsilon_k \]

(4)

where the lower case letters indicate the value of each variable scaled by region/sector specific natural logarithm of production level. In Eq. (4) \( \delta \) is now considered as the intercept, and we set \( \beta_1 = \gamma_1 \), \( \beta_2 = \psi_1 \), \( \beta_3 = \lambda \). Regarding the region/sector specific fixed effect (\( \alpha \)) we may disentangle it into two components where region and sector-specific effects are included separately (\( \alpha_0 \) and \( \alpha_k \)). In addition, Mazzanti and Zoboli (2009) state that when technology is included in an environmental efficiency function, it is interesting to separate the effects related to strict technological innovation from the effects of labor productivity gains, thus replacing the term \( \alpha_k(Y_k) \) in Eq. (4) with a properly defined labor productivity measure. In that case, according to Mazzanti and Zoboli (2009), for a given technical emission efficiency, labor productivity tends to negatively correlate with the emissions per unit of value added, thus improving EP. This result can be explained if we consider that labor productivity gains may go hand in hand with increasing capital intensity which often also corresponds to energy efficiency gains (Gruenbler et al., 1999). Given the fact that on the left-hand side of Eq. (4) there is a measure of emission intensity, if labor productivity has a positive influence on EP, \( \beta_1 \) should have a negative sign.

Turning to the effect related to technology, in a standard emission demand model it is represented by the state of technology in the production function where the more innovative firms are those that usually adopt more resource saving and/or less polluting technologies. According to Dinda (2009), technological innovation increases productivity and simultaneously it can also create potential dangers to society in the form of larger externalities related to an increasing production scale obtained by productivity gains. Since the influence of technology on labor productivity is isolated as a single term, and the scale effect is eliminated by considering an EP measure instead of emission level, the term \( t_k \) could be interpreted as the effect of technology on resource efficiency. Hence, the sign of the \( \beta_3 \) coefficient is also expected to be negative where the higher the efforts in technological innovation, the lower the emission (resource) intensity.

Finally, we expect a positive effect on EP related to stringent environmental policies (\( po_k \)), and the \( \beta_3 \) coefficient is also expected to be negative where the more stringent the regulatory framework is at regional level, the lower the emission intensity is at region/sector level.

Since recent regional economic growth models have increasingly appreciated the role of technological learning and knowledge spillovers, the role of external spillovers as potential drivers of EP should also be investigated. For instance, as emphasized by Gray and Shadbegian (2007), there is a positive correlation between the effect of extra-regional environmental regulation and regional EP. Nonetheless, to the best of our knowledge, there has been no attempt at empirical level to assess the role of regional innovation spillovers in explaining EP. To this end, Kyriakopoulou and Kepapetias (2009) find that environmental policy acts as a centrifugal force since increasing compliance costs reduce the advantage of localizing industrial activities in that region whereas knowledge externalities have a centripetal force fostering agglomeration patterns. They affirm that environmental regulation and knowledge spillovers may act as countervailing forces where firms may exploit agglomeration economies whereas environmental policy reduces this spatial concentration of economic activity. However, since environmental regulation will increase compliance costs mainly for polluting activities, a stringent regulatory framework may also act as a centripetal force, indirectly fostering an agglomeration pattern of cleaner productions via an inducement effect. To some extent, we may interpret a regional environmental regulatory setting as one of the geographical knowledge attractors, combined with standard innovation factors as dominant design and knowledge platforms (Antonelli and Colombelli, 2011). Therefore, regulation and technological innovation strategies may act coherently to generate an agglomeration effect of high-tech less-polluting activities.

Finally, according to Maddison (2006), when emissions also come from abroad (e.g., acid rain precursors as SOx in transboundary pollution effects), the existence of spatial correlation problems should be recognized and tackled. In addition to providing only a statistical spatial correlation bias, the emissions produced by sectors located in the neighboring regions may capture the role of agglomeration phenomena and EP in a different way from that of environmental regulation. To some extent, this variable is the revealed signal related to the mix of technological and organizational innovations adopted and the installed stock of capital. If, ceteris paribus, firms are located in one region that is surrounded by regions where firms adopt heavy polluting production technologies, the probability that firms will adopt cleaner production technologies will decrease so that a sort of polluting firm cluster emerges for selected geographical areas irrespective of the specific sector under investigation.

Hence, we also include in Eq. (4) a specific variable representing environmental spillovers from other regions. By considering both environmental and innovation spillovers, Eq. (4) is transformed as follows:

\[ e_k^l = \delta + \alpha_k + \beta_1 I_k + \beta_2 ES_k + \beta_3 TS_k + \beta_4 TS_k + \beta_5 Po_k + \epsilon_k \]

(5)

where \( I_k \) is labor productivity, while \( ES_k \) and \( TS_k \) represent respectively the environmental and innovation spillovers from the other Italian regions, empirically modeled as described in Section 3. Since environmental externalities are here included according to the definition of the dependent variable in the form of pollution intensity, if \( I_k \) is statistically robust, it means that choices in terms of environmental performance of the production process taken by neighboring industries play a role in internal decision in terms of EP. If the coefficient has a positive sign, it reveals the existence of agglomerative forces producing a concentration of dirty activities in circumscribed geographical areas. Otherwise, if internal emission intensity is negatively influenced by external one, some centripetal forces are predominant, as industries located in a dirty area try to become cleaner in order to capture some

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2 Induced innovation effects have been strongly linked to the origin and development of the Porter hypothesis (Lanier et al., 2011; Porter and van der Linde, 1995). There is also an increasing consensus on the potential win–win effects deriving from well combined environmental and innovation strategies (Jaffe et al., 2005). In this respect, the use of an appropriate mix of innovation and environmental policies emerges as a crucial factor in directing economic systems towards sustainable economic growth (van den Berg et al., 2007).

3 Given the geographical dimension of our case study, we consider emissions coming from other regions, while no transboundary pollution at international level is accounted for.
comparative advantages, for example related to become first comers in the green industry. Finally, we expect \( \beta_3 \) to be negative, coherently with the role played by internal innovation (\( \beta_2 \)) since we assume that the existence and diffusion of technologies from other regions will increase the probability that a more environmental-friendly production technique is available.

3. The Empirical Design of Environmental and Innovation Spillovers

The core part of the dataset is based on the Italian regional NAMEA published by the Italian National Institute for Statistics (ISTAT, 2009) for the year 2005, to our knowledge the only full regionalized NAMEA available in the EU.

Our dataset is organized as a \( (q \times n) \times 1 \) vector where \( n \) is the total number of \( k \) sectors \((\forall k = 1, \ldots, n, \text{with} \ n = 24)\) and \( q \) is the number of \( r \) regions \((\forall r = 1, \ldots, q, \text{with} \ q = 20)\), with a potential number of observations equal to 480.

When testing drivers of EP as expressed by Eq. (5), we adopt the environmental aggregation (provided by NAMEA), by which specific pollutants are summed up as greenhouse gases (GHG) and pollutants responsible for acidification process (ACID). This choice enables us to make further considerations regarding potential different impacts of the same drivers associated with environmental damages with a different geographical distribution since the effects of GHG are global whereas ACID emissions are more localized and transboundary effects may be confined to neighboring regions.

In order to represent the \( \text{IP}_3 \) term related to sector/region specific labor productivity, we compute a value added per full-time equivalent job units ratio. The two dimensions of technological innovation related to the internal variable \( \text{t}_i \) and the technology spillover effect \( \text{t}_s \), rely on a patent count approach at sectoral and regional levels. The choice of measuring technological innovation by a patent count approach is somewhat constrained by data availability. For example, Research and Development (R&D) expenditures could be a better indication of the innovative effort representing an input measurement, but unfortunately they are available at regional level without disaggregation by sectors. A second possibility might be represented by the use of the Community Innovation Survey (CIS) data produced by the EU, but the main limit is that for privacy reasons, national agencies do not release firm based datasets with the regional information needed here.

Another shortcoming concerns the fact that in this work we can only consider innovation at a general level without disentangling environmental innovation from the overall innovation activity. A potential way to solve this issue might be given by using CIS data provided by the fifth wave which considers explicitly environmental innovation adoption (as an indicator of technology diffusion). Again, matching firm-based data with regional information is forbidden for privacy reasons, while no indication on the innovative production effort is provided. This last measure could be provided by patents classified in environmental domains, as for instance relying on the IPC Green Inventory developed by the Committee of Experts of the World Intellectual Property Organization (WIPO, 2012). Committee of Experts in order to facilitate searches for patent information relating to so-called Environmentally Sound Technologies as listed by the United Nations Framework Convention on Climate Change (UNFCCC).

Contributions based on environmental innovation measured by patent statistics are increasing in the scientific literature (see among the others Dechezlepretre et al., 2011; Johnstone et al., 2010a, 2012), but they are all based on national count dataset. The regionalization of environmental IPC classes could be a rather promising future research effort.

Finally, the sector-specific innovative capacity measured by patents completely neglects the role of adoption. Innovative efforts represented by patent applications are only a portion of the overall technological advancement of firms and sectors, while in many cases product and process innovation rely on the adoption of invention produced elsewhere.

Hence, we are conscious that some substantial drawbacks characterize patents as an innovation measure. Nonetheless, previous studies at regional level have highlighted the helpfulness of patent applications as a measure of the production of innovation (Acs et al., 2002). Consequently, our output innovation measure should be considered as a first step toward the investigation of the relationship between environmental and innovation performances at regional and sectoral levels.

Patent data are drawn from the RECPAT dataset elaborated by Eurostat from the OECD PATSTAT database, gathering all patents for each region according to the 3 digit International Patent Classification (IPC) granted by the European Patent Office (EPO), geographically classified according to the postal codes of the applicants. There are 633 patent classes, and we considered all patent applications to the EPO by priority year at regional level. We adopted an ad hoc sector classification in order to assign patents (as classified by IPC codes) to specific sectors (as classified by NACE codes) relying on previous concordance proposals such as the OECD Technology Concordance and the methodology developed by Schmoehl et al. (2003), resulting in 11 available sectors (see Table A1 in the Appendix). As a result of the high variance of patenting activity over time, we considered patents in the time span 2000–2004 in order to calculate a five year average value as the best proxy of innovation stock at sectoral level with a minimum one year lag compared with emission data. The potential positive influence of innovating activities on EP arises with temporal lags since the adoption of new technologies (and consequently its effectiveness in EP terms) is not perfectly simultaneous with the invention/application itself. Bearing in mind that Eq. (5) expresses all terms scaled by value added, we computed patents to value added ratios in order to account for innovation intensity.

In order to measure technological spillovers, we first consider that the probability of innovation to spill from one region to another depends on the concentration of a particular sector in the two regions, since it is not only a matter of geographical distance that explains the existence and the strength of innovation spillovers, but also of cognitive proximity. The concept of cognitive proximity has been increasingly adopted in regional economics, since knowledge is more likely to diffuse when competences and knowledge stocks of the inventors and adopters are closely related (Quatraro, 2010). We are aware that this is still a very limited way to account for knowledge spillovers since many other exchange channels could be explored. Additionally, instead of spillovers, there...
may just be spatially correlated technological opportunities (Jaffe et al., 1993). 7

With regard to the direction and channels where knowledge spillovers occur, following empirical findings by Costa and Dechezleprêtre (2004) on technological spillovers among the Italian regions, we emphasize the role of Marshall type externalities since innovation spillovers mainly derive from firms belonging to the same industry whereas Jacob type externalities among sectors appear to be smaller for Italy. 8

In order to account for cognitive proximity, an index that captures the technological relatedness between industrial sectors by computing the similarity between two sectors’ input mix from 1–0 tables is usually adopted (Los, 2000; Los and Timmer, 2005). Since data availability on 1–0 information at sector level is limited for the Italian regions, an alternative solution is to form a similarity matrix based on technological measures as suggested by van Stel and Nieuwenhuijsen (2004).

In this paper we have built a relative specialization index (RSI) which is directly taken from relative competitive advantage formulation in order to account for the larger specialization of a specific region in selected sectors with respect to the national sector-specific average. The RSI adopted here results as follows:

\[
RSI_r^s = \frac{\frac{1}{r} \sum_{k=1}^{n} t_k^r}{\frac{1}{k} \sum_{k=1}^{s} t_k^s} \quad (6)
\]

where \( t_k^r \) is the five year average of patents to value added ratios for each k-th sector and r-th region whereas \( t_k^s \) is the same measure at national level, expressed as \( t_k^s = \sum_{i=1}^{n} t_k^s \).

The bilateral innovation spillovers (\( ts_{rs}^k \)) for each k-th sector from the s-th region to the r-th region un-weighted by the geographical distance are expressed as:

\[
ts_{rs}^k = \left( \frac{\left( RSI_r^s - RSI_r^s \right)}{\sqrt{RSI_r^s + RSI_r^s}} \right)^{-1} \quad \forall s \neq r
\]

where the first term on the right-hand side of Eq. (7) can be seen as a sort of technological proximity measure or absorptive capacity (Basu and Weil, 1998; Cohen and Levinthal, 1989, 1990) while the second term represents the technology transfer from external sources. The resulting similarity weighting matrix is explicitly designed with the aim of maintaining a sector-based disaggregation as well as a regional peculiarity.

The resulting \( (q \times q) \) matrix of spillovers for each k-th sector (with a vector of 0 in the diagonal dimension \( v_s = r \)) is then synthesized into a linear vector by using geographical distances for aggregating the sectors. The geographical distances adopted here are calculated bilaterally as the number of kilometers between the economic centers in each region, using the automatic algorithm based on highway distances with the shortest time criterion adopted by the Italian Automobile Association (ACI), which is the national official reference for distance calculation. 9

Following Bode (2004), we test three different plausible regimes: i) the “binary contiguity” concept where only neighboring regions matter for knowledge spillovers; ii) the “k-nearest neighbors” concept (testing a bound k distance of 300 km) and iii) the pure inverse distances.

First, the binary contiguity concept (\( D_1 \)) assumes that interregional knowledge spillovers only take place between direct neighbors that share a common border. We consider the first-order contiguity with direct neighbors, giving weight \( w_{rs} = 1 \) to each s-th region neighboring region r and \( w_{rs} = 0 \) to all other regions. Consequently, the variable reflecting interregional knowledge spillovers is defined as the sum of knowledge available in directly neighboring regions expressed as:

\[
D_1 t_{rs}^k = \sum_{s \neq r} \left( t_{rs}^k w_{rs} \right) \quad \text{if } s \text{ neighbouring } r \quad (8)
\]

The second spatial regime allows testing the role of knowledge spillovers strictly related to effective geographical distances and not only in terms of common border (\( D_2 \)). The maximum distance commonly found in the empirical literature leading to positive knowledge spillovers at regional level is around 300 km related to the maximum time for regular face-to-face contacts (Bottazzi and Peri, 2003). Interregional spillovers for each k-th sector and each r-th region result as follows:

\[
D_2 t_{rs}^k = \sum_{s \neq r} \left( t_{rs}^k w_{rs} \right) \quad \text{if } w_{rs} = 1 \text{ only if } D_{rs} \leq 300 \text{km, otherwise } w_{rs} = 0
\]

with \( D_{rs} \) denoting the bilateral geographical distance between the economic centers of r and s.

The third spatial regime relates to the assumption that the intensity of interregional knowledge spillovers may be subject to spatial transaction costs in the sense that the intensity of influences between two regions diminishes continuously as distance increases. In this case, the smaller the distance between r and any other region s (\( \forall s \neq r \)), the higher the weight assigned to s with respect to its influence on r. Hence, the weight assigned to each region s is proportional to the inverse distance between r and s. The variable reflecting interregional knowledge spillovers is therefore given by the distance-weighted (\( D_3 \)) sum of knowledge available in all other regions:

\[
D_3 t_{rs}^k = \sum_{s \neq r} \left( t_{rs}^k w_{rs} \right) \quad w_{rs} = D_{rs}^{-1}
\]

Since including innovation variables built on patent data reduced the number of NACE sectors in the analysis to 11, forcing us to exclude the “Electricity, gas and water supply” sector (E in NACE codes), we calculated emissions from electricity consumption for each sector as a measure of indirect emissions (bearing in mind that NACE only provides direct emissions). In this way, emissions directly associated with

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7 For example, if several patents relate to textiles in a certain region and a disporportionate fraction of the people/firms interested in textiles happen to live in that region, we would observe localization of knowledge even if proximity offers no advantage in receiving spillovers. Nonetheless, patents could be a reliable innovation measure for approximating regional knowledge externalities, at least in a broad sense (Antonelli et al., 2011). Another issue that should be considered is the product market rivalry effect of innovation activities especially related to R&D efforts (Bloom et al., 2007). R&D deprives other firms competing in the same or similar product market of future business opportunities. As opposed to knowledge spillovers, R&D then has a negative effect on other firms (for an overview of spillovers measurement issues, see Verspagen and Los, 2007).

8 The literature on innovation and agglomeration externalities remains inconclusive as to whether specialized or diversified local production structures favor local innovative activity. If Marshall type externalities are prevalent, knowledge is predominantly industry-specific. Knowledge spillovers may therefore arise between firms within the same industry and can only be supported by regional concentrations of a particular industry. If Jacob type externalities are detected, it means that knowledge may spill over between complementary rather than similar industries as ideas developed by one industry can be applied in other industries. Therefore, a diversified local production structure leads to increasing returns and gives rise to urbanization or “diversification” externalities (van der Panne, 2004). When related variety is included, Jacob type externalities also play some role in enhancing economic performance. We acknowledge that it is a consolidated result that the economy’s composition at regional level will also affect economic growth (Frenken et al., 2007) but there are many more controversies in interpreting such an influence on EP in a static framework. However, we may investigate this specific aspect further when a panel version with temporal dimension of the regional NACE dataset is available.

9 The official distances provided by ACI are computed in order to give a homogenous criterion for funding business travel costs, thus representing the best available proxy for costs of face to face contacts which are recognized as the main channel for regional knowledge spillovers.
the electricity sector are excluded and emissions due to electric power consumption are indirectly assigned to the 11 sectors, avoiding a double counting problem. We calculated electricity consumption for each sector by using data provided by Terna (the Italian major electricity transmission grid operator) and then assigning related emissions by using an average national emission intensity factor per kWh for GHG and ACID factors, with parameters equal to 0.38 and 0.016 respectively.\(^\text{10}\)

Since EP could be affected by agglomeration effects associated with a cluster-based choice of the adopted production technique, the term \(e^s\) related to environmental spillovers in Eq. (5) has been proxied by the emission intensity of the same sector in the other regions. To this end, the environmental spillovers are the sum of sectoral emissions per unit of value added from the other regions \((e^s)\) valid for \(s \neq r\), weighted by distances expressed in the three different regimes described above \((D_1, D_2\) and \(D_3\)).

Coherently with technological spillovers, the environmental spillovers were tested with three different spatial regimes as follows:

\[
D_1 e^s_{r}= \sum_{s \neq r; s \neq r} (e^s_{r})w_{rs} \quad \text{with} \quad w_{rs} = 1 \quad \text{only if} \quad s \neq r, \quad \text{otherwise} \quad w_{rs} = 0 \tag{11}
\]

\[
D_2 e^s_{r}= \sum_{s \neq r; s \neq r} (e^s_{r})w_{rs} \quad \text{with} \quad w_{rs} = 1 \quad \text{only if} \quad D_{rs} \leq 300 km \quad \text{otherwise} \quad w_{rs} = 0 \tag{12}
\]

\[
D_3 e^s_{r}= \sum_{s \neq r; s \neq r} (e^s_{r})w_{rs} = D_{rs}^{-1} \tag{13}
\]

Finally, since environmental regulation could be considered as a driver of EP (as modeled in Eq. (5)), the incidence of environmental regulation (proxied by regional public expenditures for environmental protection) on average regional income is used as a proxy (Costantini and Crepaldi, 2008). Data on environmental regulation divided into different sectors are not available, hence regional environmental regulatory frameworks allow a fixed structural effect only to be considered. Public expenditures for environmental protection may be broadly considered as the willingness of citizens to pay for preserving the natural environment, practically expressed by exploiting their voting preferences during the regional government elections for policy makers who pledge to make stronger efforts towards environmental protection (Farzin and Bond, 2006). Environmental regulation is represented by three alternative public expenditure measures: current, capital and R&D expenditures for environmental protection activities (ISTAT, 2012). Lagged variables are introduced to mitigate potential endogeneity bias due to simultaneity (see Table A2, in the Appendix, for details on variables description). We are aware of limitations in interpreting such variables since they are region-based while specific region-sector based data could provide more insightful results. As a matter of fact, if expenditures for environmental protection could be available at sector level (as the Pollution Abatement Costs and Expenditures, PACE, provided by EUROSTAT at the national level) there would be a closer correlation between the costs of regulation directly paid by firms (sectors) and the incidence effect in terms of better EP. When environmental regulation is available only at regional level, it could only be interpreted in the specific sense that it measures if and to what extent there is a pro-environmental approach in the local government, which may or may not induce the private agents to adopt environmental-friendly behaviors. Additionally, we can assume that if public institutions in a region are investing in environmental R&D activities, private firms may have interest in cooperating with public administration in several forms in order to exploit knowledge externalities in that field.\(^\text{11}\)

### 4. The Regional Patterns of Environmental Performance

#### 4.1. A First Glance at EP Geography and Drivers

Table 1 shows a first picture of EP across Italian regions and how regions behave compared with the national average when emission intensities for each pollutant are compared (by considering the whole set of polluting emissions included in NAMEA accounts) while, according to CO\(_2\) and SO\(_x\) emission intensities, Table 2 shows a quite clear and expected North–south divide.\(^\text{12}\)

Although at aggregate regional level, emission intensity is distributed accordingly with different economic levels, strong exceptions arise when the EP of industrial sectors is singled out. Figs. 1 and 2 represent the geographical distribution of labor productivity and EP, here distinguished according to two main environmental themes (climate change, as represented by GHG, and acidification, given by ACID), for two manufacturing sectors representing an energy intensive one (Fig. 1) – corresponding to the manufacture of coke, refined petroleum products and chemical products – and a high technology sector (Fig. 2), corresponding to the manufacture of machinery, electrical machinery, medical, precision and optical instruments (sectors 9 and 12, respectively, in Table A1 in the Appendix).

The two figures clearly reveal that apart from the North–south divide, there are some spatial aggregation processes both in the labor productivity and the emission intensities, but more importantly, the geographical distribution of labor productivity does not exactly correspond to the distribution of EP. We observe that environmental efficiency is heterogeneously distributed when comparing the GHG and the ACID theme as well. If we exclude Sardinia, because of its far island status, the Moran’s\(^\text{13}\) indicates the presence of spatial autocorrelation in the intensity (on the value added) of acidifying emissions (p-value 0.007) but not in the GHG emissions (p-value 0.283). These results indicate a spatial aggregation phenomenon that is significant for local pollutants (ACID) but not for global (GHG) ones.

Hence, given that the geographical distribution of polluting emissions reveals in some cases a strong spatial concentration of dirty sectors in restricted areas which may not always correspond to regions with relatively less stringent environmental regulation or lower capital and innovation intensity, a more detailed investigation of this EP spatial aggregation process is needed.

\(^{10}\) We have considered an average value at national level assuming a common energy mix for all the Italian regions, depending on the fact that the decision of the energy mix adopted for each power plant is not completely regionally based. Considering also that the electricity produced in each region may now be consumed anywhere due to electricity market liberalization, the exact energy mix related to the specific electricity consumed by firms cannot be assumed.

\(^{11}\) An example of cooperation could be represented by private–public partnerships in developing a new environmental technology which necessitates of well-established knowledge stock provided by the public institution while private firms may act as experimenters in implementing such new technology.

\(^{12}\) For the sake of brevity, preliminary analyses based on shift-share analysis (Esteban, 1972, 2000; Hoekstra and van den Bergh, 2006; Mazzanti and Montin, 2010b) are not included in this paper. Shift-share decomposition shows that if we disentangle efficiency and specialization effects, at least at the macro level, the North–South divide is, as expected, the crucial part of the story, but in addition, some sector-driven agglomerative effects seem to prevail in selected and localized areas. For example, it shows that some Central and Southern regions (Lazio and Campania) behave quite well due to a large service sector whereas some rich industrial regions (Veneto, Friuli Venezia Giulia) do not perform so satisfactorily, highlighting idiosyncrasies and criticalities that may be related to more complex issues that encompass geographical, economic and policy issues.

\(^{13}\) The univariate Moran’sI measures the type and strength of spatial autocorrelation from spatial interaction effects (e.g., externalities or spillover effects) in data distribution. This statistical measure determines the extent of linear association between the values in a given location with values of the same variable in neighboring locations.
4.2. Econometric Evidence: Environmental Performance, Innovation and Spillovers

The econometric estimations aim to investigate the relative strength of the effects associated with labor productivity, internal and external innovation drivers as well as the role of the environmental regulatory framework and the environmental spillovers on regional/sectoral EP. We test the influence of these factors for GHG and ACID emission intensity related specifications (Tables 3 and 4, respectively).

The empirical investigation relies on OLS estimations on the 11 manufacturing sectors for which patent data and statistics for electricity consumption are available (Table A1, in the Appendix), and on 19 regions – because Sardinia has been excluded considering its far island status – resulting in 209 observations. We run regressions with the robust standard error specification.

As a first outcome, we note that the impact of labor productivity on explaining the EP is economically and statistically significant in both specifications and the negative coefficient associated with this variable is interpreted as a positive correlation between productivity and environmental efficiency gains. It is an expected result that depends on the interplay of multiple drivers along the evolution of innovation, industrial and policy paths. Consistently with expectations and other analyses on NAMEA data in Italy (Marin and Mazzanti, forthcoming), this coefficient is larger (almost double) for ACID than for GHG.

We confirm that labor productivity explains all structural features in the production process such as the adoption of environmental management systems, quality control and highly efficient mechanical appraisals, which are not specifically caught by the innovative capacity, captured by patent intensity, of the economic sector. As controls, we have also included a specific variable related to energy intensity for each sector, and a dummy variable that absorbs the effect of specific dirty industries. In this way, productivity gains and innovation effects are interpreted as the real impact on environmental efficiency related to investments in technology and labor productivity drivers. It is worth mentioning that energy intensity plays a major role in shaping GHG-related EP, while dirty sector-specific features seem to be prominent in explaining environmental efficiency behavior for ACID emissions.

Secondly, environmental efficiency spillovers play a significant role in explaining EP especially for GHG emissions. The spatial regime where the environmental spillovers seem to play a major effect coincides with regions in the range of 300 km since estimated coefficients are higher for both GHG and ACID. Nonetheless, some differences emerge between the two environmental themes since, for GHG, all the three spatial regimes are statistically significant and coefficients present a small discrepancy whereas for ACID, the D₂ spatial regime seems to be the most significant.

The positive coefficient for environmental spillovers may be interpreted as the existence of clusters that are not only intended as an agglomeration of specific sectors into restricted areas, but also as an effect of the technology adopted. The lower environmental efficiency of the neighboring sectors is, the lower the internal EP of each specific sector. This means that together with the agglomeration of specific sectors into restricted areas, there is also some convergence in production processes and techniques. To some extent, the aggregation process of specific polluting sectors in relation to contiguous geographical areas is plausibly followed by common choices in the adoption of cleaner or dirtier technologies.

On the other hand, it is worth noting that the level of internal innovation, expressed as the number of sectoral patents per value added, plays no role in explaining EP since the coefficient is low and has no statistical significance in all specifications. This is plausible given that our innovation variable relates to the general efforts to produce technology, without specific environmental aims. Further research steps could be to consider specific environmental innovation rather than a general innovative capacity when the efforts by OECD and WIPO will be conclusive to a well established and consolidated methodology to classify patents for environmental protection purposes (OECD, 2008, 2011) with a regional base.

On the contrary, technological interregional spillovers seem to play a more effective role. The higher impact of innovation spillovers compared with internal innovation is again explained by the nature of our innovation variable as a general innovation output. The higher the knowledge flows from other regions, the more likely the availability of environmental-friendly technologies, and the higher the reduction in emission intensity. The portfolio of innovations available within a sector at national level (similar to the business group effect for firms discussed in Belenzon and Berkowitz, 2007) could extend the set of possible innovation choices at regional level. Firms belonging to a defined sector can eventually find the environmental-friendly innovations they need in the national framework so that intra-sector knowledge flows contribute to this aim.

Although the commented evidence may appear counterintuitive, it is a well known fact in recent analyses (Cainelli et al., 2012) that internal R&D by firms is as relevant as other external forces such as the presence...
of foreign markets, cooperation with other firms and regulations. Innovations, especially in environmental contents, appear to evolve and be adopted in open innovation systems. It is plausible that in order to deal with quite radical changes such as environmental innovations, cooperation and spillovers overwhelm internal sources. However, the need to disentangle environmental innovation from other forms of innovation is further recognized.

For innovation spillovers, the three spatial regimes all give similar and significant results, meaning that innovation effects spread out of the regional borders; the highest effect is associated with the D3 regime, meaning that the higher the availability of technological innovation at sector level, the more likely the capacity of each sector to choose the best environmentally friendly technology and the better the EP.

It is worth noting that the positive influence of technological spillovers on EP is higher for more localized pollutants (ACID). We can interpret this result by considering the closer relationship between agents causing the environmental damage and agents facing the costs. The closer this relationship, the stronger the collective reaction to induce agents causing the negative environmental externality to internalize it by adopting the innovations available in each sector more rapidly and diffusely. In this case, the size of the coefficient – its economic significance – is larger when compared with GHG, also confirming the evidence previously found for labor productivity.

Finally, with regard to the role of regional environmental expenditures (Table 5),16 we tested the role of the three alternative available measures (current, capital, and R&D public expenditures scaled by regional value added for environmental protection at regional level) introduced with one temporal lag.

Although previous findings do not change when the regulation is included, some interesting differences emerge when comparing the two environmental themes, GHG and ACID. All coefficients show an expected negative sign since an increase in the social price of negative externalities would force firms to adopt more efficient production processes but, for GHG, only R&D public expenditures for environmental protection seems to positively influence EP.

On the contrary, the regulatory framework seems to be more effective for ACID emissions since all the three measures have a positive and significant influence on environmental efficiency gains. Empirical results seem to reinforce the evidence on the stronger capacity of the collective policy action to force the local government to adopt more stringent environmental standards and rules when there is a higher perception of damage from the community.

The evidence for GHG is additionally explained by the well known weakness of Italian climate policy effectiveness (Johnstone et al., 2010b, 2010c).

4.3. Robustness Checks

In order to gather relevant policy suggestions from our empirical exercise, we have carried several robustness checks.

First, a multicollinearity problem may arise if regional innovation is explained by spillovers, as a standard result in regional economic convergence literature. In order to check for the robustness of our model, we tested potential multicollinearity of internal and external innovations of

---

16 Regional environmental expenditures – available from official ISTAT sources – capture a specific feature of environmental regulations, and are associated with a citizen’s willingness to pay for abating emissions.
the regressor explaining regional innovation by performing the Variance Inflation Factor (VIF). All average VIF values are far below 5.00, which is the minimum threshold level revealing a multicollinearity problem.

Second, since potential endogeneity may arise in the innovation variable, we have performed the Hausman test on the two alternatives, a standard OLS and an instrumental variables (IV) estimator where region/sector based patents are instrumented by spillovers and other common variables (as R&D private and public efforts). Hausman statistics clearly do not reject the hypothesis that the OLS estimator provides coefficients almost equal to the IV one. The OLS therefore remains consistent and efficient.

Third, since spatial correlation may also bias the results due to the inclusion among the regressors on the r.h.s. of Eq. (5) of the spatial lag of the dependent variable, we implemented spatial dependence diagnostics. The spatial weights matrix used to test the presence of spatial dependence are based on a rook weights matrix (a contiguity-based matrix) for the Italian regions initially calculated with the Geoda 0.9.5-i software. For the Italian regions, the spatial weights matrix used to test the presence of spatial autocorrelation among the regressors on the r.h.s. of Eq.(5) of the spatial lag model is equal to the one obtained each time for the number of considered sectors. Thus, the final weights matrix has the same number of observations as the considered cross-sector-region dataset (Anselin, 2003).

As a final robustness check, we tested the potential effects of the neighboring environmental regulatory system in line with Gray and Shadbegian (2007): no significant effect on emission intensity is found. Regional internal regulation effects prevail, when significant.

### 4.4. A Spatial Simultaneous Model

A final investigation is aimed at tackling the potential endogeneity of the spatially lagged term, namely the environmental spillover. Referring to Anselin (2003) in his discussion on conditional and simultaneous spatial models and structural and reduced form, we claim that the procedure we chose in this work by inserting an assumed exogenous spatially lagged dependent variable, is usually adopted in spatial statistics (Cressie, 1993). This is a conditional model, which does not explain the effects of

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17 A “trick” for obtaining a spatial weights matrix is to replicate the initial one – opportu-

18 For the sake of simplicity, we have not reported all results in the paper but they are

19 We thank a referee for this useful comment.
neighboring locations in the model. It uses spatially lagged dependent variable covariates to control for some of the spatial issues. Both independent and spatially lagged dependent variables explain the spatial pattern of dependent variable. As alternative, simultaneous models \- which are more often implemented in spatial econometrics and applied economics \- present only the vector of explanatory variables in the explanation of the dependent variable. A reduced form is thus estimated, where a complete spatial pattern is explained: that is ‘the interactions between all observations, observed simultaneously’ (Anselin, 2003, p.157). This simultaneity means that we treat endogeneity by taking into account the fact that each location is in turn a neighbor for its neighbors. More technically, the covariance structure is compatible with a spatial pattern in the final reduced form where we correct for spatial effects.

In this paragraph we present the estimation of a spatial simultaneous model. We first check for spatial dependence and eventually correct OLS estimates. Table 4 shows a set of new estimations for all the specification we have in Tables 3 and 4 (for GHG and ACID emissions, respectively). Despite these new specifications do not contain in the right hand side the spatially lagged term (in our model represented by the environmental spillovers) and the regional dummies, the results are not altered with respect to the previous ones.\footnote{A unique exception is represented by specification 6 (both for GHG and ACID emissions) in which only the D2 technological spillovers loses its statistical significance.} This finding reveals that the variable environmental spillovers are able to capture a certain spatial correlation that could be present in the model, almost in the same way of a spatially corrected model. With this variable, the diagnostic for spatial dependence suggests (with significant Robust LM tests) using a spatially corrected model only in the case of GHG emissions, but not in the ACID emission case. The correction of OLS estimates (GHG: specifications 5, 6 and 7) for spatial dependence confirms all the previous findings. Moreover it is confirmed that there is a clear distinction between environmental performance referred to GHG or ACID emissions. In the case of ACID emissions, the spatial proximity of regions does not reflect a common or similar environmental performance suggesting that for local polluters each region could propose and force the intra-region productive activities to follow specific and local rules: contiguity of regions, in this case, is not a pro-active factor.

### 5. Conclusions

The achievement of positive environmental performance at national level could strongly depend on differences in local capabilities and conditions and on consequent environmentally and technologically related spillovers. The Italian North–south divide, considering both the industry specialization and the efficiency components, affects regional EP. On the one hand, such strong North–south differences in performance may reflect coherence with economic development stages and priorities but, on the other hand, can also signal regulatory and industrial policy failures or successes occurring even at similar income per capita levels. Industrial regional specialization matters but efficiency peculiarities also play a crucial role. The North-East as a whole, an important economic area in the country driven by export intensive manufacturing sectors, appears to perform worse than the Western part of the industrialized North. Traditional elements of the Italian North–south divide are not the only ones that explain regional EP in Italy.

### Table 4

<table>
<thead>
<tr>
<th>Dep var ACID</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor productivity</td>
<td>$-1.543^{***}$</td>
<td>$-1.383^{***}$</td>
<td>$-1.301^{***}$</td>
<td>$-1.213^{***}$</td>
<td>$-1.201^{***}$</td>
<td>$-1.139^{***}$</td>
<td>$-1.051^{***}$</td>
</tr>
<tr>
<td>Internal innovation</td>
<td>$(-6.16)$</td>
<td>$(-5.32)$</td>
<td>$(-5.73)$</td>
<td>$(-4.76)$</td>
<td>$(-4.61)$</td>
<td>$(-4.94)$</td>
<td>$(-3.93)$</td>
</tr>
<tr>
<td>Energy intensity</td>
<td>$-0.019$</td>
<td>$-0.017$</td>
<td>$-0.013$</td>
<td>$-0.010$</td>
<td>$-0.006$</td>
<td>$-0.010$</td>
<td>$0.004$</td>
</tr>
<tr>
<td>Dirty sector dummy</td>
<td>$0.404^{***}$</td>
<td>$0.373^{***}$</td>
<td>$0.358^{***}$</td>
<td>$0.352^{***}$</td>
<td>$0.398^{***}$</td>
<td>$0.389^{***}$</td>
<td>$0.392^{***}$</td>
</tr>
<tr>
<td>Environ. spillovers D1</td>
<td>$2.559^{***}$</td>
<td>$2.727^{***}$</td>
<td>$2.034^{***}$</td>
<td>$2.155^{***}$</td>
<td>$2.247^{***}$</td>
<td>$2.088^{***}$</td>
<td></td>
</tr>
<tr>
<td>Environ. spillovers D2</td>
<td>$0.163^{*}$</td>
<td>$0.162^{**}$</td>
<td>$0.195^{**}$</td>
<td>$0.191^{**}$</td>
<td>$0.162^{**}$</td>
<td>$0.191^{**}$</td>
<td></td>
</tr>
<tr>
<td>Tech. Reg. spillovers D1</td>
<td>$0.109$</td>
<td>$(1.35)$</td>
<td>$0.106$</td>
<td>$(1.11)$</td>
<td>$(1.10)$</td>
<td>$(1.96)$</td>
<td></td>
</tr>
<tr>
<td>Tech. Reg. spillovers D2</td>
<td>$-0.134^{**}$</td>
<td>$-0.240$</td>
<td>$-0.111^{**}$</td>
<td>$-0.229$</td>
<td>$-0.204^{***}$</td>
<td>$-3.12$</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>$4.596^{***}$</td>
<td>$4.423^{***}$</td>
<td>$3.489^{***}$</td>
<td>$4.228^{***}$</td>
<td>$3.281^{***}$</td>
<td>$2.833^{***}$</td>
<td>$2.865^{***}$</td>
</tr>
<tr>
<td>Regional dummies</td>
<td>$4.51$</td>
<td>$4.21$</td>
<td>$4.47$</td>
<td>$4.89$</td>
<td>$4.51$</td>
<td>$4.36$</td>
<td></td>
</tr>
<tr>
<td>No obs.</td>
<td>209</td>
<td>209</td>
<td>209</td>
<td>209</td>
<td>209</td>
<td>209</td>
<td></td>
</tr>
<tr>
<td>Adj R-sq</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.78</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>F-stat</td>
<td>47.96</td>
<td>49.87</td>
<td>54.32</td>
<td>49.8</td>
<td>49.8</td>
<td>54.90</td>
<td></td>
</tr>
<tr>
<td>Root MSE</td>
<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td></td>
</tr>
<tr>
<td>Average VIF value</td>
<td>1.70</td>
<td>1.78</td>
<td>1.80</td>
<td>1.78</td>
<td>1.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LM (lag)</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>LM (error)</td>
<td>0.68</td>
<td>0.71</td>
<td>0.79</td>
<td>0.44</td>
<td>0.87</td>
<td>1.12</td>
<td></td>
</tr>
</tbody>
</table>
| Notes: ***, **, * for p-values < 0.01, 0.05 and 0.1 respectively; robust t-stat values in parentheses. For Hausman and spatial diagnostic tests (LM (lag) and LM (error)) p-values in parentheses.
### Table 5
The role of environmental expenditures.

<table>
<thead>
<tr>
<th>GHG</th>
<th>ACID</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Labor productivity</td>
<td>$-0.501^{***}$</td>
</tr>
<tr>
<td>Internal innovation</td>
<td>(2.94)</td>
</tr>
<tr>
<td>Energy intensity</td>
<td>0.009</td>
</tr>
<tr>
<td>Dirty sector dummy</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Environ. spillovers D1</td>
<td>0.567***</td>
</tr>
<tr>
<td>Environ. spillovers D2</td>
<td>(1.141)</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D1</td>
<td>0.976***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D2</td>
<td>0.236***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D3</td>
<td>0.125***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D4</td>
<td>0.016</td>
</tr>
<tr>
<td>Internal Innovation</td>
<td>0.009</td>
</tr>
<tr>
<td>Dirty sector dummy</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Environ. spillovers D1</td>
<td>0.567***</td>
</tr>
<tr>
<td>Environ. spillovers D2</td>
<td>(1.141)</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D1</td>
<td>0.976***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D2</td>
<td>0.236***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D3</td>
<td>0.125***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D4</td>
<td>0.016</td>
</tr>
<tr>
<td>Environ. spillovers D1</td>
<td>0.567***</td>
</tr>
<tr>
<td>Environ. spillovers D2</td>
<td>(1.141)</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D1</td>
<td>0.976***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D2</td>
<td>0.236***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D3</td>
<td>0.125***</td>
</tr>
<tr>
<td>Tech. Reg. spillovers D4</td>
<td>0.016</td>
</tr>
</tbody>
</table>

Notes: ****, **, * for p-values < 0.01, 0.05 and 0.1 respectively; robust t-stat values in parentheses.

### Table 6
Spatial simultaneous model.

<table>
<thead>
<tr>
<th>GHG</th>
<th>ACID</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Labor productivity</td>
<td>$-0.739^{***}$</td>
</tr>
<tr>
<td>Internal Innovation</td>
<td>(5.12)</td>
</tr>
<tr>
<td>Energy Intensity</td>
<td>0.638***</td>
</tr>
<tr>
<td>Dirty Sector dummy</td>
<td>(16.84)</td>
</tr>
<tr>
<td>Tech. Reg. Spillovers D2</td>
<td>1.332***</td>
</tr>
<tr>
<td>Tech. Reg. Spillovers D1</td>
<td>$-0.088^{***}$</td>
</tr>
<tr>
<td>No obs.</td>
<td>209</td>
</tr>
<tr>
<td>Adj R-sq</td>
<td>0.81</td>
</tr>
<tr>
<td>F-stat</td>
<td>39.60</td>
</tr>
<tr>
<td>Root MSE</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Notes: ****, **, * for p-values < 0.01, 0.05 and 0.1 respectively; robust t-stat values in parentheses.

* Spatial Error Model.
into selected geographical areas may be associated with common choices in the adoption of cleaner or dirtier technologies, evidence which helps us to explain why the same sector specialization into different regions may be characterized by different emission intensities or efficiency as we found in the descriptive analysis too.

A second important result is that technological interregional spillovers seem to play a more effective role in improving environmental efficiency than internal innovation, with an increasing effect for more localized pollutants. In this case, the greater overlapping of polluters and agents perceiving environmental damage for more localized emissions also allows explaining the stronger effectiveness of environmental regulation at regional level in fostering environmental efficiency gains.

Acknowledgments

The authors thank the members of the Environmental Accounting Unit of the Italian National Statistical Institute (ISTAT) – Cesare Costantino, Aldo Femia, Angelica Tudini and Giusy Vetrella – for their very valuable work in providing regularly the NAMEA series and their useful methodological support. We also gratefully acknowledge the valuable comments and suggestions on previous versions of this work made by participants at the seminars and conference (c/o IEFE Bocconi University, Milan, University of Roma Tre, Rome, UNI-MERIT, Maastricht and EAERE Conference, Rome) held in 2011. We are grateful to Antonio Musolesi and Roberto Zoboli for specific hints.

Appendix

Table A1
Concordance classification for NACE sectors, NAMEA sectors and IPC codes.

<table>
<thead>
<tr>
<th>NAMEA code</th>
<th>NACE code</th>
<th>IPC code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A – agriculture</td>
<td>A01</td>
</tr>
<tr>
<td>4</td>
<td>DA15 – manufacture of food products and beverages</td>
<td>A21-A22-A23-A24-C12-C13</td>
</tr>
<tr>
<td>5</td>
<td>DA16 – manufacture of tobacco products</td>
<td>A41-A42-D01-D02-D03-D04-D05-D06</td>
</tr>
<tr>
<td>6</td>
<td>DB18 – Manufacture of wearing apparel; dressing; dyeing of fur</td>
<td>A43-B68-C14</td>
</tr>
<tr>
<td>7</td>
<td>DD00 – Manufacture of wood and of products of wood and cork, except furniture</td>
<td>A44-A45-A46-A47-A63-B09-B27-B29-C02-C30-G10</td>
</tr>
<tr>
<td>8</td>
<td>DE21 – Manufacture of pulp, paper and paper products</td>
<td>B31-B42-B43-B44-D21-G09</td>
</tr>
<tr>
<td>9</td>
<td>DF23 – Manufacture of coke, refined petroleum products and nuclear fuel</td>
<td>C01-C05-C06-C07-C08-C09-C10-C11-C40-F16</td>
</tr>
<tr>
<td>10</td>
<td>DG24 – Manufacture of chemical and chemical products</td>
<td>B28-B32-C03-C04</td>
</tr>
<tr>
<td>11</td>
<td>DJ27 – Manufacture of basic metals</td>
<td>B25-B26-C21-C22-C23-C25-D07-E02-E05</td>
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<tr>
<td>12</td>
<td>DJ31 – Manufacture of fabricated metal products, except machinery and equipment</td>
<td>B27-B28-C21-C22-C23-C25-D07-E02-E05</td>
</tr>
</tbody>
</table>

Source: own elaborations on Schmoch et al. (2003).

Table A2
Variables description and main statistics.

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Full description</th>
<th>No Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GHG</td>
<td>GHS emissions (CO₂, CH₄, and N₂O converted in tonnes of CO₂) per full-time equivalent job units</td>
<td>454</td>
<td>3.68</td>
<td>1.62</td>
<td>0.23</td>
<td>7.91</td>
</tr>
<tr>
<td>Acid</td>
<td>ACID emissions (NOₓ, SOₓ, NH₃) per full-time equivalent job units</td>
<td>454</td>
<td>1.01</td>
<td>1.73</td>
<td>-2.66</td>
<td>5.96</td>
</tr>
<tr>
<td>Labor productivity</td>
<td>Value added per full-time equivalent job units</td>
<td>456</td>
<td>3.75</td>
<td>0.56</td>
<td>1.74</td>
<td>5.46</td>
</tr>
<tr>
<td>Environ. Spillovers</td>
<td>Sector-specific pollutant emissions in directly neighboring regions Eq. (11)</td>
<td>437</td>
<td>-0.14</td>
<td>1.70</td>
<td>-5.43</td>
<td>3.61</td>
</tr>
<tr>
<td>Environ. Spillovers</td>
<td>Sector-specific pollutant emissions in regions ≤ 300 km maximum distance Eq. (12)</td>
<td>436</td>
<td>4.90</td>
<td>1.66</td>
<td>0.34</td>
<td>8.61</td>
</tr>
<tr>
<td>Environ. Spillovers</td>
<td>Sector-specific pollutant emissions in all regions Eq. (13)</td>
<td>460</td>
<td>0.76</td>
<td>1.57</td>
<td>-3.26</td>
<td>3.92</td>
</tr>
<tr>
<td>Energy intensity</td>
<td>Electricity consumption to value added ratio for each specific sector</td>
<td>380</td>
<td>3.30</td>
<td>1.35</td>
<td>-2.34</td>
<td>7.26</td>
</tr>
<tr>
<td>Env.Reg.Curr.Exp.</td>
<td>Environmental regional expenditure 2004 (current) per valued added</td>
<td>460</td>
<td>0.38</td>
<td>0.90</td>
<td>-0.99</td>
<td>2.73</td>
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<tr>
<td>Env.Reg.Cap.Exp.</td>
<td>Environmental regional expenditure 2004 (capital) per valued added</td>
<td>460</td>
<td>0.90</td>
<td>1.05</td>
<td>-0.72</td>
<td>2.85</td>
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<tr>
<td>Env.Reg.R&amp;D.Exp.</td>
<td>Environmental R&amp;D regional expenditure 2004 per valued added</td>
<td>460</td>
<td>-4.81</td>
<td>1.62</td>
<td>-8.32</td>
<td>2.95</td>
</tr>
<tr>
<td>Internal innovation</td>
<td>Number of patents per value added; five-year average 2000-2004</td>
<td>280</td>
<td>0.13</td>
<td>3.57</td>
<td>-6.91</td>
<td>6.17</td>
</tr>
<tr>
<td>Tech. Reg. Spillovers</td>
<td>Sector-specific innovation spillovers from patents intensity (five-year average 2000–2004) available in directly neighboring regions Eq. (8)</td>
<td>280</td>
<td>0.54</td>
<td>3.17</td>
<td>-6.91</td>
<td>5.76</td>
</tr>
<tr>
<td>Dirty Sector dummy</td>
<td>Dummy for heavy polluting sectors as explained in footnote No 14</td>
<td>460</td>
<td>0.30</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
modelling to approximate carbon and other ‘footprints’ of EU27 consumption for 2000 to 2006. EUROSTAT, Luxembourg.


