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Geography, environmental efficiency and economic growth: how to uncover localised externalities through spatial econometric modelling

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*Abstrac*t: Over the past fifteen years an increasing interest has risen for assessing the extent to which the pursuit of economic growth and a cleaner environment are convergent rather than conflicting objectives. The present paper aims to test the hypothesis that environmental degradation and per capita income follows an inverted-U-shaped relationship (the so-called Environmental Kuznets Curve) at the Italian Nut3 level, a more than intermediate framework between macroeconomic and microeconomic considerations, over the period 1990-2005. We adopt a spatial econometric approach by means of which it is possible to account for the localised nature of environmental and knowledge externalities. In this spatial-adapted EKC, we explicitly introduced the role of *structural change*. The experiment is expected to highlight major differences between geographical clusters from the point of view of "ecological efficiency" depending on the strength of the underlying industrial structure (i.e. "agglomerated" areas of cumulative growth due to dynamic increasing returns) and to enhance further local differences depending on the local character of the different air pollutants considered.

Keywords: Environmental Kuznets curves; Economic growth; Spatial econometrics; global and local pollutants.

JEL classification: C21, O13, Q20

1. Economic growth and environmental degradation

Over the past fifteen years an increasing interest has risen for assessing the extent to which the pursuit of economic growth and a cleaner environment are convergent rather than conflicting objectives (Grossman and Krueger, 1992). Although empirical results vary for different pollutants and model specifications, initially there was evidence that the level of environmental degradation and per capita income follows the same inverted-U-shaped relationship as income inequality and per capita income do in the well-known Kuznets Curve (Kuznets, 1955). That's why the relationship between environmental degradation and per capita income had been called *Environmental Kuznets Curve* (EKC; Panayotou, 1993). However, as the body of literature on EKC

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grown, it emerged that no simple, predictable relationship between an aggregate measure of environmental quality and per capita income can be identified (Stern, 1998; Plassmann and Khanna, 2006).

Anyway, the EKC hypothesis represents a long-term relationship and sum up a fundamentally dynamic process of change, a single-economy development path characterized by different stages *over* time. Clearly, this development trajectory can be observed over time or in cross-region cross sectional data representing several countries/regions with different levels of income corresponding to their emission levels. That's why, although the EKC hypothesis is fundamentally a *within*-country story, the most part of empirical support has come almost exclusively from cross-country data, which mainly preferred time series or panel approaches (Grossman and Krueger, 1992; Grossman and Krueger, 1995; Panayotou, 1997; De Bruyn, 1997; Vincent, 1997; Toras and Boyce, 1998; Barrett and Graddy, 2000). In fact, if we assume that each country/region follows its EKC, then at any cross section of time, we should observe some relatively poorer countries/regions at their initial stage of EKC, some developing ones approaching towards peak or start to decline, and others relatively richer at their falling stage of EKC.[2]

However, it must be pointed out that ecological and environmental economists seem to have ignored the geographical dimension of such a significantly heterogeneous empirical relationship. At the same time, economic geographers mainly ignored the environmental dimension of the landscape of production, that is to say, the casual relationship going from the spatial allocation of economic activity to growth and the environment. Given the lack of integration between two fields of studies (environmental economics and economic geography) that in our view should be considered as complementary, initially our effort focused on the fundamentally geographical and dynamic nature of the EKC relationship.

Hence, even though closely related to the environmental Kuznets curve literature, our approach substantially differs from previous empirical works, which did not pay enough attention to the spatial dimension of pollution phenomena. In fact, if an EKC were to exist, it would be strongly affected by local specific factors such as factor endowments, differences in technology, infrastructures, climate, *etc*..[3] Notwithstanding, the vast majority of EKC's empirical papers use panel data structures which estimates a common functional form to all countries/regions "up to

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[2] It must be pointed out that testing the EKC hypothesis by pooling time series and cross-section data, and assuming homogeneity in its slope coefficients, implies a significant loss of local data variability and heterogeneity.

[3] Moreover, as far as cross-section analysis are concerned, the EKC may simply reflect "the juxtaposition of a positive relationship between pollution and income in developing countries/regions with a fundamentally different, negative one in developed countries, not a single relationship that applies to both categories of countries" (Vincent, 1997, p. 417).

some deterministic vertical shift specific to every country/region of year of the panel”[4] and assume spatial-stationarity. Moreover, given their macroeconomic cross-country approach, these works lacked to consider the presence of relevant industry specific determinants of pollution intensity.

That is why we test a “spatially” adapted EKC hypothesis at the Italian Nut3 regional level[5] (i.e. provinces), a more than intermediate level between a macro and a micro approach which allows a better match between income and the pollution data (Deacon and Norman, 2004). As air pollution tends to be more concentrated near its source, in fact, local income seems the more appropriate measure of scale to be considered. Moreover, as some Italian regions are marked by relatively high levels of spatial agglomeration, intra-local business networking, innovation and growth, the chosen methodological approach should enhance the geographical dimension of the relationship under study. In fact, Italian economic activity still tend to be clustered in well defined industrial districts, a features stressed during the ‘80s by the main representative of the Italian school of Economic Geography, Becattini (Scott, 2000). Thus, our “spatially” adapted EKC is expected to highlight major differences between Italian geographical clusters from the point of view of “ecological efficiency” depending on the strength of the underlying industrial structure, and to enhance further local differences depending on the local character of the different air pollutants considered.

In order to capture the local nature of the relationship under study, we adopt a Geographically Weighted Regression (GWR) model (Fotheringham *et al.*, 2002). This methodology is particularly appropriate in the Italian case as it permits to account for spatial non-stationarity arising from the persistence of industrial “agglomerated” areas and per capita income divergences between Italian Central Northern and Southern provinces[6] (Graziani, 1978; Saraceno, 1983) a development pattern which could be interpreted as a consequence of cumulative causation forces in operation (Hirschman, 1958; Myrdal, 1957).

While accounting for the complexity of the EKC hypothesis, the aim of our analysis is to capture major changes of the localized relationship that have occurred over time. That’s why the EKC hypothesis has been tested for t equal to 1991, 1996, 2001 and 2005 for four major air pollutants with different relevance at the spatial scale. That is to say, carbon dioxide (CO_2) and methane

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[4] Ordás Criado (2007), p. 1.

[5] NUTS stands for Nomenclature of Territorial Units for Statistics used by Eurostat. In this nomenclature NUTS2 refers to Basic Administrative Units whose first level of disaggregation gives rise to NUTS3 Territorial Units, i.e. provinces.

[6] In this paper we define Italian Central-Northern regions Lazio, Tuscany, Umbria, Marche, Emilia-Romagna, Liguria, Valle d’Aosta, Piedmont, Lombardy, Trentino A.A., Friuli Venezia-Giulia, Veneto. The southern regions are Campania, Abruzzi, Molise, Puglia, Basilicata, Calabria, Sicily and Sardinia which represent the so-called “Mezzogiorno”.

(CH_4), usually referred to as “global pollutants”, and carbon monoxide (CO) and non methane volatile organic compounds (NMVOC), usually referred to as “local pollutants”.[7]

Finally, to control for structural change, namely the existence of different degrees of transition towards a lower carbon emission economy at the local level, we introduce the specialization in energy intensive sectors as exogenous variable. To define them we referred to the European Emission Trading Scheme,[8] Directive 2003/87/CE, which defines “energy intensive industries”[9], energy, ferrous metals, cements and lime, glass, ceramics, pulp and paper sectors.

The paper is organized as follows. Section 2 reviews the main contributions on the EKC. Section 3 discusses the spatial structure of data, examines several spatial econometric issues and the use of GWR (3.1). This material is included for completeness, but most of the details can be skipped by those readers who are more interested in the practical applications. Furthermore, section 3 presents the augmented spatially-adapted EKC model (3.2). Section 4 adopts the GWR approach to test the spatially adapted EKC at the Italian Nuts 3 regional level and Section 5 concludes the paper.

2. Theoretical explanations behind the EKC

The main conclusion of the large empirical body on the EKC relationship is that no simple, predictable relationship between an aggregate measure of environmental quality and per capita income has been identified. Instead, the EKC has been found to hold only for a subset of environmental measures (Stern, 1998; Plassmann and Khanna, 2006).

Research on the EKC began with the analysis of panel data on 42 countries to identify an EKC effect for different measurements of air quality (Grossman and Krueger, 1993). Similarly, Selden and Song (1994) found support for an EKC for SO^2, while both Grossman and Krueger (1995) and Shafik and Banyopadhyay (1992) found a monotonic inverse relation between water and per capita income, and a positive one between carbon emissions and per capita income. Since these initial studies, many have followed, focusing specifically on air pollution (i.e. List and Gallet, 1999; Heerink et al., 2001; Cole, 2003; Khanna, 2002; Bruvoll et al., 2003; Deacon and Norman, 2006; Merlevede et al., 2006; water pollution (Torras and Boyce, 1998; Paudel et al., 2005), deforestation (i.e. Culas, 2007; Rodriguez-Meza et al., 2003; Heerink et al., 2001; Barbier, 2001), hazardous waste and toxins (i.e. Gawande et al., 2001; Rupasingha et al., 2004), carbon dioxide (CO_2)

[7] Moreover, differently from the most part of previous empirical studies, we use relative measures of pollution intensity.
[8] The Directive 2003/87/CE of the European Parliament and of the Council of the 13th October 2003 created a trading scheme of greenhouse gases (GHG) emissions allowances within European Union.
[9] In 2005, these sectors accounted for the 58% of Italian greenhouse gas emissions (GHG) while representing only the 0,07% of Italian workers.

(Azomahou et al., 2006) among others (see Cavlovic et al., 2000; Dasgupta et al., 2002; Copeland and Taylor, 2004 for reviews).

As the EKC hypothesis achieved credibility as a stylized fact, an increasing more theoretically-oriented literature emerged. Within it, some works adopted a macro approach trying to explain the socio and macroeconomic mechanisms behind the EKC (Selden and Song, 1995; Cole et al., 1997; Suri and Chapman, 1998; Agras and Chapman, 1999; Andreoni and Levinson, 2001; Pasche, 2002; Bimonte, 2002; Roca, 2003; Dinda, 2005), while few others preferred a more micro-based approach aimed to explain the linkages between environmental innovation and firms' performances (Porter and Van der Linde, 1995; Brunnermeier and Cohen, 2003; Mazzanti e Zoboli, 2005).[10]

The "macro" strand of this theoretically-oriented literature on EKC identified three main channels through which economic growth affects the quality of environment: the scale of production, structural change, and technological progress. Concerning the first, *ceteris paribus*, at higher levels of GDP correspond higher levels of pollution as increasing output requires more inputs, thus more natural resources are used up in the production process.[11] The negative impact of the scale effect on the environment has a propensity to prevail during the initial stages of growth, but it will eventually be outweighed, over time, by the positive impact of the structural and technological change,[12] which tend to lower the emission level (Vukina *et al*., 1999). Furthermore, as income grows, people achieve a higher standard of living and care more about the quality of the environment where they live.[13] Once individuals reach a given level of income, they start demanding a cleaner environment creating a demand pressure for environmental quality and innovation (Porter and Van der Linde, 1995) which is seen as a *luxury* good. Hence, the higher the level of per capita income, the higher the income elasticity of environmental quality demand (Pezzey, 1989; Selden and Song, 1994;

[10] Given the existence of several reviews of the EKC literature (Stern, 1998; Dasgupta *et al*., 2002; Cole, 2003; Copeland, 2004; Dinda, 2004; Stern, 2004), the present paper does not attempt to go over the empirical and theoretical evidence again.

[11] As Condoo and Dinda (2008) stressed, in the EKC literature the role of income distribution is mainly ignored, while it may play an important role in the determination of environmental quality. For a discussion see Torras and Boyce (1998), Scruggs (1998), Magnani (2000).

[12] With reference to technological change, the literature stressed that it may consist both in a more efficient use of inputs or in a substitution of less for more environment friendly inputs, and/or in a shift *within* a sector toward new less environmentally harmful process or product, less generation of waste, and in transformation of wastes to less environmentally harmful forms (Komen *et al*., 1997; Galeotti, 2007). In Italy, over the period 1997-2006, the data shows that the of *end-of-pipe* investments, a form of pollution control and not of pollution prevention, represented more than the seventy percent of the firm's investments in environmental protection. Clearly, this pattern of investments and its distribution over the different means of environmental protection is deeply influenced by environmental policies and incentives, and by the firm's structural characteristics. The concentration of Italian firm's environmental investments on air and climate protection, for example, could be the result of both the implementation of international agreements and of their small dimension which make it easier to internalize these forms of pollution control, reached through process innovations, rather than water and industrial waste disposal services which need integrated technologies.

[13] Moreover, technology oriented and demand oriented innovation dynamics may coexist. In fact, environmental oriented new demands are a component of the structural change occurring along economic development (Saviotti and Pika, 2004; Mazzanti and Zoboli, 2007), a point of view which may support the idea of a positive relationship between social capital "endowment" and environmental quality.

Baldwin, 1995) which is generally recognized being in excess of unity. As Hill and Magnani (2002) emphasized, rather than being a natural consequence of economic development, the EKC is a consequence of choosing priorities (Torras and Boyce, 1998; De Bruyn, 2000).[14] Regarding the *third* channel, structural change, a number of works (Grossman and Krueger, 1991; Lucas *et al*., 1992; Vukina *et al*., 1999) underlined that environmental degradation tends to increase as the structure of an economy changes from agricultural to industrial, but it starts falling as it changes from energy intensive industry to knowledge-based industries and services.[15] This view lays emphasis on the importance of structural change from energy-intensive heavy industry to services which are characterized by a lower environmental impact.[16]

The recent micro-strand of the literature deals with environmental innovation, environmental regulation and economic performance, and emphasizes the need for a deeper understanding of the complex and peculiar nature of environmental innovation and its influence on firms' performance, criticizing the mainly macro approach which prevailed so far. However, this adapted EKC hypothesis at a microeconomic level, which would capture the relationship between economic activity agglomeration and environmental quality at the local level, where emissions are generated, can not be easily tested because of the lack of emission data at establishment levels. Nevertheless, some authors (Mazzanti and Zoboli, 2007) tested an adapted EKC hypothesis where the link under study was the correlation between labour productivity (value added per employee), and environmental efficiency (emissions per unit of value added) at a sector level. In their work, they found evidence of a negative correlation between labour and environmental efficiency for Italy over the period 1990-2002 explaining it through the so-called potential "double externalities" issue (Jaffe *et al.*, 2005). That is to say, increasing environmental efficiency by environmental innovations may

[14] Dasgupta *et al*. (2002) argued that there are three main reasons why richer countries regulate pollution more strictly. Firstly, pollution damage gets higher priority after society had already invested in health and education. Secondly, higher income societies have better technical personnel and wider budgets for enforcement and monitoring activities. Thirdly, higher income and higher education level empower local communities to enforce higher environmental standards. *See* also Galeotti (2007).

[15] As far as Italy is concerned, in 2005 the 77% of greenhouses gas (GHG) emissions were produced by total industry (including construction and energy), the 22% by the service sector, and the 11% by agriculture, even though they represented, respectively, the 41%, the 57%, and the 2% of Italian production. In the same year, the energy intensity (at ppp) of Italian industry was 0,116 (0,11 in 1990) and in the Italian service sector was 0,016 (0,014 in 1990; *source*: Enerdata).[15] Hence, over the last fifteen years, the energy intensity of both industry and services increased but given the change from industry to services and the relatively lower energy intensity of the latter, a negative correlation between economic growth and environmental pressure is found. In fact, if an index of decoupling is calculated over the period 1991-2005 for Italy, we find an overall value close to one, suggesting that decoupling occurred.

[16] A slightly modified view emphasized the role of *technological life cycles*: economies pass from polluting technology to high technology as obsolete and dirty technologies are substituted with cleaner ones (Galeotti, 2006).

strengthen competitiveness and firm performance with or even without a policy “incentive”[17], hence labour and environmental efficiency are complement: firms may simultaneously increase the level of production and lower bad outputs.[18]

However, as several shortcomings, such as the lack of a micro-based theoretical background, the lack of disaggregated data, and the fact that the empirical results are often sensitive to the nations chosen, the pollutant measurement adopted, trade effects, functional form, and methodological choice (Caviglia-Harris *et al*., 2009; Harbaugh et al., 2002; also see Cavlovic et al., 2000) emerged, the EKC started being strongly criticized (Muller-Furstenberger and Wagnerb, 2007; Perman and Stern, 2003).

To sum up and stress where our contribution is going, it can be said that due both to the predominant *macro-and-ecological-oriented* approach to the EKC hypothesis and to the lack of data at more disaggregated levels, the literature on EKC did not stress the local dimension of the relationship under study and given the predominant cross-country methodological approach did not take into consideration its spatial heterogeneity. That is to say, firstly there is the need for a theoretical approach which recognizes that both economic growth and its environmental impact are *per se* a non-linear phenomenon deeply rooted at the local level and influenced by the existence of cumulative forces and dynamic increasing returns which are the main cause of industrial agglomeration phenomena. Secondly, there is the need for an econometric approach by means of which to account for the localised nature of environmental externalities and for spatial heterogeneity. Even though this paper is mainly empirical, we hope and aim to contribute to fill up these “holes”.

3.1 Modelling the local income-pollution relationship: the GWR model

In recent years a renewed interest has been growing among geographers about the specific relevance of methods for spatial data analysis. Along the lines of the extensive existing literature on “local” approaches to the study of data variability (Hardle, 1991; Barnett *et al*., 1990), the issue of spatial variation in the geographical space has been brought to the fore in socio-economic modelling.

[17] Clearly, the innovative endogenous strategy of firms regarding environmental resources depends on the features of environmental goods (they can be characterized by private appropriable rents and by public elements) and on the technology adopted.

[18] This is known as the “asymmetric case” (Collins and Harris, 2005).

Unlike physical processes, social processes are usually not constant over space, bearing a certain amount of spatial non-stationarity. Assessment of data variability across space must take into account the association between each data measurement and the location at which the measurement is taken. However, if the data generating process is non-stationary over space, global statistics which summarise major characteristics of a given spatial data configuration might be very misleading locally due to a bias in the estimates. In these terms even those measures of spatial dependency, such as the Geary and Morans'I coefficients (Moran, 1948; Geary, 1954), whose aim is to detect the tendency of spatial data to cluster in space, yield approximate indications from a local perspective averaging out different degrees of spatial variation around different locations. The same applies to model fitting, as model parameter estimates relate to the study area as a whole and inference on these might lead to poor understanding of the relationship investigated if this exhibits significant local spatial variation.

The need for models that allow for spatially varying coefficients has led researchers to develop several types of local analytical techniques to deal with spatial non-stationarity. In geographical literature, considerable attention has recently focused on the GWR technique proposed by Fotheringham, Brundson and Charlton (Fotheringham *et al*., 2002), the use of which is now widespread in the field of the social sciences. Spatially varying coefficient models have also been developed in the statistical literature following a Bayesian approach (Gelfand *et al*., 2003), but so far their scope has proved to be limited, receiving negligible attention in geographical literature (Wheeler, 2006).

The methodological framework underlying GWR is quite similar to that of local linear regression models well-known in statistical literature, as it uses a kernel function to calculate weights for the estimation of local weighted regression models (see Loader, 1999; Hastie *et al*., 2001). Nonetheless, major differences are represented in GWR by the application of the kernel weighting scheme and by the methodological focus. In fact, kernel weighting is applied to observations in geographical rather than attribute space, and the methodological focus is concerned with assessing local variation in the regression coefficients, rather than data smoothing as in a spatial local regression techniques.

In contrast to the general regression model $\mathbf{y} = \mathbf{X}\beta + \varepsilon$, where the regression coefficients are location invariant, the specification of a basic GWR model, for each calibration location, s=1,…,n, is:

$$y(s) = X(s)\beta(s) + \varepsilon(s) \tag{1}$$

where y(s) is the dependent variable at location s, X(s) is the row vector of explanatory variables at location s, β(s) is the column vector of regression coefficients at location s, and ε (s) is the random error at location s. Hence, regression parameter estimates are allowed to vary according to location in space, implying that each coefficient in the model is now a function of *s*, a point within the geographical space of the study area. The regression coefficients are estimated for each calibration location by weighted least squares yielding the following vector of estimates:

$$\hat{\beta}(s) = [X^T W(s) X]^{-1} X^T W(s) y \tag{2}$$

where X = [X(1);X(2);…;X(n)] ^{T} is the design matrix of explanatory variables, including a column of 1's for the intercept; W (s) = diag [w1(s), …, wn(s)] is the diagonal weights matrix that is calculated for each calibration location; y is the nx1 vector of dependent variables; and $\hat{\beta}(s)$ = ($\hat{\beta}_{s0}, \hat{\beta}_{s1}, ..., \hat{\beta}_{sp}$) is the vector of p+1 local regression coefficients at location *s* for *p* explanatory variable and intercept. As a result $\hat{\beta}(s)$ gives rise *to a map of local estimated parameters*.

Like kernel density estimation (Silverman, 1986) the weighting scheme is expressed as a kernel function that places more weight on the observations closer to the calibration location s. Among the many specifications of the kernel function (Fotheringam et al. 2002), one of the most commonly used, and the one used in the present study, is the bi-square nearest neighbour function:

$$W_j(s) = \begin{cases} \left[1 - \left(d_{sj}/b\right)^2\right] & if \quad j \in \{Ns\} \\ 0 & if \quad j \notin \{Ns\} \end{cases} \tag{3}$$

where d_{sj} is the distance between the calibration location s and location j, b is the distance to the N*th* nearest neighbour (i.e. the spatial bandwidth), and the set {Ns} includes the observations that are within the distance of the N*th* nearest neighbour. Weights for all observation beyond the N*th* one are set to zero and the weight for observation s is 1.[19]

Major worries arise, however, when inference has to be carried out on GWR local parameter estimates in order to determine whether spatial heterogeneities do in fact characterize the underlying data generating process. As potential dependencies may arise between the local regression coefficients associated with different exogenous variables and with the intercept and the covariate coefficients as well, cautious interpretation of the spatial patterns of local GWR coefficients is preferable. Depending on the severity of the problem encountered, substantive interpretation of the local GWR estimates could be flawed or even made impossible. Although

[19] This kernel is clearly of an adaptive kind as its spatial bandwidth adjusts to the varying sparseness of data points across the territory under study. Using this kernel ensures against model calibrations on very few data points – a situation that occurs frequently in socio-economic applications and that, in extreme cases, can even make the estimation of some parameters impossible due to insufficient variation in small samples.

typical of the well-established diagnostic issues commonly addressed in standard global regression analysis, this topic has been tackled only recently (Wheeler and Tiesfelsdorf, 2005; Wheeler, 2007). On the other hand, a great deal of attention has been dedicated to testing individual parameter stationarity adopting a Monte Carlo approach[20], or less computationally intensive formal test statistics for spatial nonstationarity and heterogeneity (Leung *et. al.* (2000a, 200b)[21]. Moreover, thorough investigation into the question of dependency among local regression coefficients in GWR has shown that collinearity may arise even in presence of uncorrelated exogenous variables in the data generating process. Thus, preliminary examination of GWR local regression coefficient estimates appears to be essential to ascertain if these are correlated and to establish if the relationships found are meaningful in terms of the problem investigated or an "artifact of the statistical method" (Wheeler and Tiefelsdorf, 2005, p.169).

3.2 The estimated equation

As we have already seen, there are three main explanations of the environment and growth relationship. Firstly, the *stages of economic growth*: environmental degradation tends to increase as the structure of the economy changes from being agriculture-based to industry and then to service-based. Secondly, a slightly modified view stresses the role of *technological life cycles*, that is to say, economies pass from polluting technology to high technology: obsolete and dirty technologies are substituted with cleaner ones.[22] Finally, a great deal of attention has been devoted to the income effect resulting from the consideration of *environment as a luxury good*: once individuals reach a given level of income (or consumption), they begin to demand increasing investments in an improved environment, hence, they create a demand pressure for environmental innovation.

In order to take into account the role of structural change differently from what the literature on EKC has done (Panayotou, 1997; Dinda *et al*., 2000; Friedl and Getzner, 2003; Komen *at al*., 1997), we introduced in a canonical environmental Kuznets curve the ratio of the number of workers in energy intensive sectors to the number of industrial workers. This variable takes into account the structure of the economy; to define the energy intensive sectors we refer to the European Emission Trading Scheme, Directive 2003/87/CE, which consider energy, ferrous metals, cements and lime, glass, ceramics, pulp and paper sectors as high-emission ones. Further, we

[20] This test is based on the sampling distribution of the standard deviation of the GWR parameter estimate under the null hypothesis that the parameter of interest is globally fixed (Fotheringham *et al.*, 2002 p. 93).
[21] It should be noted, however, that misleading inference due to correlation between regression coefficients arises also in the Bayesian modelling. In this framework the correlation is only modelled, but no simulation test is performed "to ensure that the model is estimating the true parameters correctly" (Wheeler, 2006, p. 9).
[22] This happens, in general, when a country can afford to spend more on research and development.

introduce population density, given its typical relevance to various forms of pollution at the local level. The estimated equation is the following:

$$y_{i,t} = \hat{\beta}_0 + \hat{\beta}_1 + GDPpc_{i,t} + \hat{\beta}_2 \left(GDPpc_{i,t}\right)^2 + \hat{\beta}_3 \left(GDPpc_{i,t}\right)^3 + \hat{\beta}_4\, ind\_mix_{i,t} + \hat{\beta}_5\, pd_{i,t} + \varepsilon_{i,t} \qquad i = 1 \ldots 103$$

where y_{it} is the ratio of emissions to the number of industrial workers in province *i* at time *t*, $GDPpc_{i,t}$ is per capita income in province *i* at time *t*, $ind\_mix_{i,t}$ is the ratio of the number of workers in energy intensive sectors in province *i* at time *t* to the number of industrial workers in province *i* at time *t*; $pd_{i,t}$ is the population density; e_{it} is the error term. The two ratios y_{it} , $ind\_mix_{i,t}$ are built on the same aggregate variable in order to take into account the whole degree of industrialisation in each province. The source for the number of the industrial workers at the Nut3 level is the national census of industry (1991, 1996, 2001[23]).

Model (1) allows testing several different forms of the environmental damage-growth relationship. In particular, if:

$\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_3 = 0$	No relationship between environmental damage and per capita income;
$\hat{\beta}_1 > 0$ and $\hat{\beta}_2 = \hat{\beta}_3 = 0$	A monotonic increasing relationship or a linear relationship between environmental damage and per capita income;
$\hat{\beta}_1 < 0$ and $\hat{\beta}_2 = \hat{\beta}_3 = 0$	A monotonic decreasing relationship between environmental damage and per capita income;
$\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$ and $\hat{\beta}_3 = 0$	An inverted-U-shaped relationship, namely, the EKC;
$\hat{\beta}_1 > 0$, $\hat{\beta}_2 < 0$ and $\hat{\beta}_3 > 0$	A N-shaped relationship;
$\hat{\beta}_1 < 0$, $\hat{\beta}_2 > 0$ and $\hat{\beta}_3 < 0$	Opposite to the N-shaped relationship.

[23]The geographical structure of industrial workers in 2001 has been also used to obtain estimates from the aggregate number of industrial workers in 2005.

4. Results

According to the GWR estimation approach, if a relationship between variables is distinctively represented at the local level, then significant differences should emerge in greater evidence in the local parameter estimates than in the global ones. Regression results are therefore provided for both global and local estimation and compared for all the years investigated. In section 4.1, we show and interpret the results of global estimation and major improvements obtained through GWR estimation, while in section 4.2 deeper of analysis of local estimation is carried out separately for each pollutant considered[24].

4.1. Major spatial trends

As far as global estimates are concerned (tables 1-1a), major differences can be noticed between the model fit of the global pollutants (CO_2 and CH_4) and that of the local pollutants (NMVOC and CO). All global regressions yield higher fit of the data in the case of local pollutants (NMVOC and CO) with R squared values between 0.4 and 0.6. Regarding the global pollutants (CO_2 and CH_4), the goodness of fit is slightly higher for CH_4, with R squared values stable around 0.35.

Relevance of the GWR estimation emerges for all the pollutants investigated with higher goodness of fit and significant F values of the ANOVA GWR model test[25] (tables 2-5). These results confirm the need for proper consideration of the inherent spatial nature of air pollutants. As far as global regressions are concerned, the good fit of the data for local pollutants appears to be a consequence of the spatial scale of their impact with respect to the emission sources. However, the spatial dimension of these pollutants is not captured, and the interpretation of the relationship investigated could be even seriously biased. Instead, the significant improvement of the GWR model fit for all the pollutants considered points out that spatial non-stationarity is a crucial aspect to take into account.

As previously recalled, variability of socio-economic process across space is usually characterized by spatial non-stationarity and this appears to be the case of the EKC hypothesis, given the key role played by the economic development process as a driver of major structural changes of the aggregate demand including its evolution towards higher quality standards. As a consequence, in the following sub – section we will give a detailed discussion of the EKC model fit for each of the pollutants considered with special attention to the relevant mapped GWR estimation parameters.

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[24] As far as local regression parameter estimates are concerned, and according to the caveats recalled for the interpretation of GWR results, spatial patterns have been preliminary examined with respect to correlation.
[25] The ANOVA tests the null hypothesis that the GWR model represents no improvement over a global model.

Tab 1. Global regression results.

	1991	1996	2001	2005	1991	1996	2001	2005
	CO^2				CH^4			
R^2 adjusted	0.28	0.22	0.24	0.29	0.32	0.32	0.33	0.3
AIC	1203.2	1256.3	1260.9	1280.6	-13.7	41.7	29.66	25.92
Intercept	-26.86	-414.8	105.5	295.6	2.1	1.92	2.1	2.04
	(-0.064)	(-0.753)	-0.2	-0.425	(5.86)	(4.44)	(5.43)	(4.56)
Per capita income	0.0048	0.0832	-0.012	0.036	-0.0003	-0.0002	-0.0002	-0.0001
	-0.116	-0.726	(-0.15)	(-0.35)	(-4.29)	(-2.61)	(-3.71)	(-3.09)
Per capita income^2	-0.00000075	-0.000005	-0.0000003	-0.0000001	0.0000001	0.0000003	0.0000003	0.0000001
	('0.067)	(-0.700)	(-0.086)	(-0.25)	(3.82)	(1.99)	(3.01)	(2.51)
Per capita income^3	-0.00000000002	-0.00000000001	-0.00000000006	-0.00000000006				
	-0.067	-0.62	(-0.086)	(-0.22)				
Energy intensive sectors	8.22	9.71	10.87	12.4	0.0046	0.002	0.0045	0.005
	(6.074)	(5.02)	(5.08)	5.86	(1.24)	(0.53)	'(0.83)	(1.03)
Population density	0.105	0.116	0.117	0.086	-0.0006	-0.0007	-0.0005	-0.0006
	(-1.75)	(1.53)	(-1.48)	(-1.02)	(-3.59)	(-3.38)	(2.48)	(-2.84)
	CO				NMVOC			
R^2 adjusted	0.61	0.54	0.56	0.48	0.46	0.5	0.38	0.32
AIC	220.8	277.5	202.76	220.3	-69.18	-60.9	-95.12	-104.34
Intercept	4.25	5.85	3.319	2.59	1.1	1.15	0.7	0.61
	(-3.81)	(4.31)	(3.70)	(2.26)	(4.03)	(4.37)	(3.13)	(2.58)
Per capita income	-0.0006	-0.00063	-0.0002	-0.0002	-0.0001	-0.00009	-0.00004	-0.00004
	(-2.77)	(-3.47)	(-3.097)	(-2.16)	(-2.48)	(-2.68)	(-1.72)	(-1.64)
Per capita income^2	-0.00000000002	-0.00000000002	-0.00000000005	-0.00000000002	0.0000000	0.0000000	0.0000000	0.0000000
	-1.76	(2.50)	(2.10)	(1.53)	(1.58)	(1.63)	(0.81)	(0.98)
Energy intensive sectors	0.088	0.097	0.09	0.093	0.012	0.013	0.01	0.1
	(7.62)	(5.81)	(7.18)	(7.52)	(4.24)	(4.07)	(3.50)	(4.16)
Population density	0.002	0.002	0.0015	0.0012	0.0003	0.0003	0.0003	0.0002
	(3.404)	(2.53)	(3.18)	(2.41)	(2.59)	(2.44)	(2.62)	(2.01)

*Notes: t values in brackets; *statistical significance at the 10% level;*
statistical significance at the 5% level;statistical significance at the 1% level.*

Tab 1a. Global regression results.CO2

	2001	2005
R^2 adjusted	0.24	0.29
AIC	1258.6	1278
Intercept	63.29	149.19
	(0.42)	(0.76)
Per capita income	-0.0054	-0.013737
	(-0.34)	(-0.72)
Per capita income^2	-0.000000	0.00000
	(-0.003)	(0.39)
Energy intensive sectors	10.864	12.38
	(5.10)	(5.89)
Population density	0.117	0.087
	(1.5)	(1.02)

*Notes: t values in brackets; *statistical significance at the 10% level;*

While accounting for complexity of the EKC hypothesis, the aim of the analysis is to capture major changes of the localized relationship that have occurred over time. Due to the relatively stable structure of Italy's GDP spatial trend, as well as of the main related aspects of the underlying production system (such as the degree of industrialization), the dynamics of the localised spatial pattern of the GWR parameter estimates can be interpreted in the light of the specific "environmental efficiency" that a given area has been able to develop.

4.2. Local estimates

CO_2

Tab 2. Geographically Weighted Regression results, Geodesic distances, CO ^{2}

	1991	1996	2001		2005	
	geodesic distances	geodesic distances	geodesic distances		geodesic distances	
R^2 adjusted	0.33	0.38	0.3	0.281511	0.3	0.31
F	3.00	2.42	2.34	2.45	3.12	1.69
Intercept - Median	10.2*	-4255.6****	'-458.1	-84,348	-547	-95,585
Per capita income - Median	-0.02**	0.71****	0.05	0.011563	0.0'76	0.009647
Per capita income^2 - Median	0.00003**	-0.00015****	-0.000004	0.000000*	-0.000004	0.000000*
Per capita income^3 - Median	0.00000**	0.00000****	0.000000	-	0.000061	-
Energy intensive sectors - Median	5.5	5.54	6.6	6.8	14.66	9.9
Population Density	0.072	0.04	0.09	0.092182	0.03	0.061923

*Notes: *Monte Carlo test significance at the 10% level; **Monte Carlo test significance at the 5% level; ***Monte Carlo test significance at the 1% level; **** Monte Carlo test significance at the 0.1% level*

As far as CO_2 emissions are concerned, the results of the local fit of the EKC equation point out the very global nature of this pollutant. Although the improvement of the GWR estimation over the global regression is significant, the goodness of fit yields R squared values mostly around 0.3. No improvement is recorded for the intercept term either. It is never found significant in the global regressions and significance is found in local estimates only in 1991 and 1996. Moreover, careful attention should be paid to the large values of the local intercept estimates found in 1996, as they might be revealing of the complex character CO_2 and hence of other major factors which have not been presently included in the model.

More insights into the CO_2 EKC relationship are given by the examination of the regression parameter estimates. In all global regressions both GDP and population density parameters estimates are never found significant, while the "energy intensive sector" parameter estimates are highly significant with the expected (positive) sign. Instead, in the GWR estimation the GDP per capita parameters are always found significant. Significance of local GDP parameter estimates is found in 1991, and particularly in 1996, up to third order. In 2001 and 2005 only slight significance is found up to second order.

Results from mapped t surfaces of the local parameter estimates, allow for deeper consideration of the "shape" of the localized relationship found. All the t maps show that the localized character of the EKC found for CO_2 is the compound effect of different local behaviours with opposite (north, south) spatial tendencies in most cases. With the only exception of 1996, where an only N shape behaviour is found, inverse U behaviour are found in the South in 1991, and in the North, in 2001 and 2005.

CH_4

As formerly recalled, a comparison of the results obtained for CO_2 and CH_4 from GWR estimation of the EKC hypothesis is legitimated by their common nature of “global” pollutants..

Tab 3. Geographically Weighted Regression results, Geodesic distances, CH^4

	1991	1996	2001	2005
	geodesic distances	geodesic distances	geodesic distances	geodesic distances
R^2 adjusted	0.46	0.54	0.63	0.5
F	3.78	5.16	9.23	5.87
Intercept - Median	0.98****	1.62****	1.63****	1.40****
Per capita income - Median	-0.0001***	-0.00007****	-0.0001****	-0.0004****
Per capita income^2 - Median	0.0000056**	0.00000064****	0.00000228****	0.00000**
Energy intensive sectors - Median	0.006	0.003	0.005	0.013
Population Density	-0.0007	-0.001	-0.001	-0.0011

*Notes: *Monte Carlo test significance at the 10% level; **Monte Carlo test significance at the 5% level; ***Monte Carlo test significance at the 1% level; **** Monte Carlo test significance at the 0.1% level*

However, a deeper examination of the GWR regression performed on CH_4 points out the presence of remarkable differences between these two global pollutants with respect to the structure of the whole relationship both at the global and the local level. The global fit of the EKC relationship is in fact higher than in CO_2 with major differences concerning the number, significance and sign of the GDP parameter terms - a stable U shaped behaviour being found- and the population density, which is always found highly significant with negative sign.

At the local level, the analysis of the GWR parameter estimates depicts quite a more complex behaviour with a highly localized U shaped relationship, as clearly shown by the p significance of the local estimates. Significance of the local relationship is evident from the t surfaces of the local GDP estimates which point out the important contribution of southern areas and the “composition effect” of the underlying production system due to the significant role played by the agriculture sector in CH_4 emissions.

NMVOC

As far as NMVOC and GDP relationship is concerned, the estimation results suggested a U shaped relationship both at the global and the local level. Because of the local character of this pollutant, as expected, the improvement of the goodness of fit is much less remarkable than in the case of global pollutants. Local GDP parameter estimates appear to be quite significant in southern areas and show a south-north spatial trend, while the "energy- intensive sector" parameter estimates are significant only at the global level, as well as the population density parameter estimates.

Tab 4. Geographically Weighted Regression results, Geodesic distances, NMVOC

	1991	1996	2001	2005
	geodesic distances	geodesic distances	geodesic distances	geodesic distances
R^2 adjusted	0.64	0.52	0.43	0.36
F	3.25	2.59	2.65	2.59
Intercept - Median	1.136***	0.73*	0.57	0.33**
Per capita income - Median	-0.0006***	-0.0001**	-0.00008*	-0.00001**
Per capita income^2 - Median	0.000004***	0.0000023**	0.0000013*	0.00000**
Energy intensive sectors - Median	0.002	0.008	0.008	0.008500
Population Density	0.0003	0.0002	0.0002	0.00016

*Notes: *Monte Carlo test significance at the 10% level; **Monte Carlo test significance at the 5% level; ***Monte Carlo test significance at the 1% level; **** Monte Carlo test significance at the 0.1% level*

These results may be better interpreted by the light of the decrease of the goodness of fit which is observed in the global regression, as the R squared values range from 0.50 in 1996 to 0.32 in 2005. Given the local character of the pollutant considered, this seems to suggest an effective impact of regulations on "environmental efficiency". The lower significance found for the local GDP parameter estimates seems also to be consistent with such a hypothesis**.**

CO

Tab 5. *Geographically Weighted Regression results, Geodesic distances, CO*

	1991	1996	2001	2005
	geodesic distances	geodesic distances	geodesic distances	geodesic distances
R^2 adjusted	0.82	0.85	0.83	0.86
F	5.08	7.74	6.2	8.9
Intercept - Median	4.07****	5.00****	2.75****	1.44****
Per capita income - Median	-0.0005****	-0.0004****	-0.0002****	-0.002****
Per capita income^2 - Median	0.0000163****	0.00000634****	0.000003****	0.0000024****
Energy intensive sectors - Median	0.17	0.03	0.02	0.025000
Population Density	0.001	0.0006	0.0005	0.0006

*Notes: *Monte Carlo test significance at the 10% level; **Monte Carlo test significance at the 5% level; ***Monte Carlo test significance at the 1% level; **** Monte Carlo test significance at the 0.1% level*

Among all the pollutants considered, CO shows the highest fit of the GWR estimation with increasing R squared values scoring over 0.8 in 2005. The fit of the global regressions is instead rather stable with R squared values mostly around 0.5 and only with a slight decrease from 1991 to 2005**.**

The global relationship is found significant for the GDP parameter according to a U shaped behaviour, and for the "energy intensive" sector variable and the population density, with a positive (expected) sign. However**,** the GWR estimates of the GDP parameter appear to be the compound result of a U shaped behaviour in the North and the opposite in the South, with higher local significance for the latter.

5 Concluding remarks

The present paper aimed at estimating a "spatially" adapted EKC hypothesis in order to account for the spatial dimension which is inherent to pollution phenomena and to capture its changes *over* time. The estimation has been carried out for *t* equal to 1991, 1996 , 2001 and 2005 at the Italian Nut3 regional level (i.e. provinces) with a *geographically weighted regression* (GWR) approach.

The empirical findings presented in this study give account of a significant relationship between the evolution of per capita GDP and four different measures of air pollution intensity: CO_2 emissions per industrial worker, CH_4 emissions per industrial worker, NMVOC emissions per industrial worker and CO emissions per industrial worker. In particular, the results obtained from the assessment of the localized relationship through GWR spatial estimation highlight the prominent influence of various local specific factors related to the structure of the underlying economic system. On the other hand the impact of the “energy intensive” sectors, which have been explicitly introduced in the model as a control variable, is captured mainly at the global level as an “average effect”, hence confirming their absolute relevance for which they gained attention in the environmental regulation. The same applies to population density which never holds significance at the local level. It has mainly a scale effect which is specific to single pollutants.

At the local level a U shaped “average” relationship predominates. However, for all the pollutants investigated, the localised behaviour of the estimated relationship gives often insights on the emergence of clustered areas where the relationship tends to diverge from the prevailing behaviour. This seems to suggest the existence of more and less “environmental efficient” areas which tend to cluster. In this regard it should be also noticed that southern regions often behave opposite to the northern ones, hence highlighting the role of the local context in development dynamics. Somewhat more complex results have been obtained in the case of CO2. Despite the local relevance of GDP estimates, there are not clear indications of stable behaviours of the EKC relationship, suggesting that further investigation should be carried out on this specific pollutant.

Although far from being conclusive, the present analysis suggests that the EKC view should be considered more critically: a major role is played by externalities at the local level with respect to the structure of the underlying economic system, and further work should go more in depth on this.

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