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Estimating the environmental Kuznets curve for ecological footprint at the global level: A spatial econometric approach

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ABSTRACT

The national ecological footprint of both consumption and production are significantly spatially autocorrelated at global level. This violates the assumption of independently distributed errors of most conventional estimation techniques. Using a spatial econometric approach, this paper re-examine the relationship between economic growth and environmental impact for indicator of ecological footprint. The results do not show evidence of inverted U-shape Environmental Kuznets Curve. The domestic ecological footprint of consumption (or production) was obviously influenced by the ecological footprint of consumption (or production), income and biocapacity in neighborhood countries. We also found that the consumption footprint is more sensitive to domestic income, while production footprint is more sensitive to domestic biocapacity, which is often unnoticed in EKC hypothesis analyses that focus exclusively on the consumption-based or production-based indictors.

1. Introduction

Over the past decades, there has been considerable interest in analyzing the relationship between economic growth and environmental impact. They have tried to find out whether or not environmental pressure is rising with national income at low income levels, but falling at higher income levels. If the underlying phenomenon exists, such an inverted U-shaped relationship between economic growth and environmental impact is known as the Environmental Kuznets Curve (EKC). Since the early 1990s, heated debates have been made on the EKC hypothesis, and plenty of empirical studies support the inverted-U relationship (Beckerman, 1992; Shafik and Bandyopadhyay, 1992; Cropper and Charles, 1994; Selden and Song, 1995; Grossman and Krueger, 1996; Panayotou, 1999; Canas et al., 2003; Roca, 2003; McPherson and Nieswiadomy, 2005; Liu et al., 2007). According to several empirical studies, technological innovation, structural change toward information-intensive industries and services, increased environmental awareness and higher environmental expenditures play important roles in shaping the EKC (Grossman and Krueger, 1996; Suri and Chapman, 1998; Vukina et al., 1999; Antweiler et al., 2001; Liddle, 2001; Pasche, 2002; Cole, 2004; Auci and Becchetti, 2006). However, more and more recent researches have cast doubt on the concept of empirical results, and evidence of the existence of the EKC has also been questioned (Rothman, 1998a; Grether and Melo, 2002; Roca, 2003; Dinda, 2004; Bagliani et al., 2008; Romero-Avila, 2008; Kearsley and Riddel, 2010). Some evidence shows that if there was an inverted U-shaped relationship it might be partly or largely a result of the effects of trade on the distribution of polluting industries (Arrow et al., 1995; Stern, 2004). More specifically, International trade provides the means by which 'dirty' industries can be moved from the developed regions to the developing regions (Cole, 2004).

EKC has now been estimated for a variety of environmental indictors including air pollution, water pollution, deforestation, hazardous waste and toxins, carbon dioxide, biodiversity conservation and ecological footprint (Shafik and Bandyopadhyay, 1992; Kaufmann et al., 1998; Rothman, 1998a; Bhattarai and Hammig, 2001; Stern, 2004; Galeotti et al., 2006; Managi, 2006; Culas, 2007; Bagliani et al., 2008; Caviglia-Harris et al., 2009; Leitao, 2010). At its most basic the technique involves regressing per capita emissions or concentrations on income per capita and its squared value with panel data (Maddison, 2006). Although panel data are more informative and have greater degrees of freedom, spatial dependence is a problematic aspect of many panel data sets in which the cross-sectional units are not randomly sampled. Usually, one observation in a sample of cross-sectional observations depends on other cross-sectional observations (Rupasingha, 2009). Anselin and Griffith (1988) describe this as the existence of a functional relationship between what happens at one point in space and what

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happens elsewhere, which violates standard statistical techniques that assume independence among observations.

Spatial effects are important in evaluating the impact of economic growth on environmental quality (Giacomini and Granger, 2004). On the one hand, many of the subjects in the environmental issues are inherently spatial. The spread of contaminated water, the diffusion of air pollution, and the spread of invasive species all lead to the spatial autocorrelation problem in statistics (Raymond and Arno, 2003). In reality, most data sets used to estimate EKC contain elements of both being composed of repeated observations on countries (Maddison, 2006). On the other hand, countries can interact strongly with each other through channels such as trade, technological diffusion, capital inflows, and common political, economic and environmental policies (Ramirez and Loboguerrero, 2002). Some studies have suggested that the shape of the EKC is a consequence of high-income countries in effect exporting their pollution to lower-income countries through international trade (Cole, 2004). In such cases, externalities can spillover the limits among countries, contributing in the explanation of environmental effects of economic growth. Anselin and Rey (1991) recognized such forms of spillover effects as cases of substantial spatial dependence and ignoring these spatial relationships would weaken our ability to generate meaningful inferences about the processes we study.

Several authors have recently pointed to the importance of spatial dimensions in environmental measures (Bockstael, 1996; Goodchild et al., 2000; Anselin, 2001; George and Nickolaos, 2011). According to Cliff and Ord (1981), while causal factors form an essential part of the underlying process, the inclusion of spatial components is likely to be important to an understanding of the problem analyzed. Even from an analytical perspective, these spatial effects are also important because they may invalidate certain standard methodological results (Anselin and Rey, 1997; Anselin, 1988; Ying, 2003). Raymond and Arno (2003) pointed out that once spatial dependency had been discovered, it is obviously a need to specify a spatial statistical model accounting for such spatial effects and to use an appropriately spatially adapted estimator. Spatial regression models provide ways to test and accommodate various forms of dependence among observations. Following, among others, the pleas of Bockstael (1996) and Anselin (2001) to explicitly incorporate space in the analysis of environmental topics, a small literature is now emerging. Nowadays, spatial econometric models have begun to make inroads into the study of environmental policy and natural resource management.

Although cross-sectional units or geographical areas form the basic unit of analysis in most EKC studies, the spatial data analysis techniques was underused in this topic for a long time. Ignoring spatial considerations may lead to incorrect inferences and poor model performance. This particular shortcoming has been recognized by Rupasingha et al. (2004), who first incorporate spatial correlation structures into analysis of the relationship between per capita income and toxic pollution in the US counties. Then the spatial econometric analysis of the EKC is gradually starting off by considering air pollutants (Maddison, 2006) and species imperilment (McPherson and Nieswiadomy, 2005; Pandit and Laband, 2007). However, to our knowledge, there have no reports about applications of the spatial econometric technique to examine the EKC for ecological footprint, a powerful indicator for measuring and communicating environmental impact and sustainable resource use. Maddison (2006) suggested that further studies of the EKC using spatial econometric approach are still necessary to better understand the unobserved spatial dependence across countries.

The objectives of this paper were thus to explore systematically the use of spatial econometric techniques in estimating EKC for ecological footprint. We begin with a conventional EKC estimation to find a linear relationship between dependent and independent variables and get a range of diagnostics for spatial autocorrelation description. Then, this paper expands the analysis by incorporating spatial variables in our models and re-examining the claim for the EKC. In addition, the difference in the spatial correlation of national ecological footprints between consumption and production has been performed finally.

2. Methods and materials

2.1. Methods

Cross sectional data are often associated with each other, this is a spatial autocorrelation. Specification testing for spatial autocorrelation is typically performed with the asymptotic distribution of Moran's *I* test statistic, which depends on the spatial weight matrices that reflect the intensity of the geographic relationship between observations in a neighborhood (Anselin and Bera, 1998). Methodological background for Moran's *I* test statistic and spatial weight construction can be found in many econometrics texts and will not be covered here.

Spatial econometric models may present themselves in a variety of types. Models can be estimated with cross-sectional as well as panel data. Inadequacies in the available data relating to the footprint and biocapacity accounts for all the countries involved in our analysis in time series having led to the condition that the cross sectional models are the approach that I would take throughout the remainder of the paper. Two types of cross sectional models have been used: spatial lag models and spatial error models. The spatial lag model in matrix form is given by:

$$Y = \alpha + \rho WY + X\beta + \varepsilon \qquad (1)$$

where Y is a vector of dependent variables, X is a matrix of explanatory variables, W is the spatial weight matrix, α and ρ are scalar parameters, β is a vector of parameters and ε is a normally distributed disturbance term with a diagonal covariance matrix.

An alternative way of incorporating spatial relationships is through spatial dependence in the error term. This refers to a situation in which the errors associated with any one observation are a spatially weighted average of the errors at nearby sites plus a random error component. The spatial error model is given by:

$$Y = \alpha + X\beta + \varepsilon, \quad \varepsilon = \lambda W\varepsilon + u \qquad (2)$$

where λ is the autoregressive coefficient.

Maddison (2006) proposes that the spatial error model can also be approximated by an autoregressive lag in both the dependent and independent variables. Then we extend the model in (2) to a spatial Durbin form, which is written as:

$$Y = \rho WY + X\beta_1 + WX\beta_2 + \varepsilon \qquad (3)$$

where β_1 and β_2 are the associated parameter vectors.

The model shown in (3) is referred to as a spatial Durbin model by Anselin (1988) due to the analogy with a suggestion by Durbin for the case of a time series model with residual autocorrelation (LeSage, 1999). Spatial regression models cannot be estimated by OLS estimators for the problem of residual covariance. It must instead be estimated using maximum likelihood techniques. In this analysis, the Moran's I test statistic, spatial lag and error models were estimated using GeoDa 0.9.5-I, and spatial Durbin models were estimated using LeSage's Spatial Econometrics MATLAB toolbox.

2.2. Materials

The Ecological Footprint Atlas 2008 (Ewing et al., 2008) developed by Global Footprint Network, provide a detailed accounting