Testing Increasing Returns to Pollution Abatement in Pesticides

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1. Introduction

The Environmental Kuznets Curve (EKC) proposes that there is an inverted U-shaped relationship between a specific measure of environmental pollution and per capita income levels. Starting with the seminal work of Grossman and Krueger (1993, 1995), a number of empirical studies have examined this relationship for various pollutants, regions, and time periods. Researchers have found an inverted U-shaped relationship, monotonically increasing or decreasing, between pollution and a rising per capita income level. Stern (2004) and Yandle et al. (2004) have provided a summary and discussions of the empirical literature (see also Selden and Song, 1994; Ekins, 1997; the special issue of *Ecological Economics*, 1998; Stern, 1998; Ansuategi and Perrings, 2000; Cavlovic et al., 2000; Anderson and Cavendish, 2001; Antweiler et al., 2001; Bulte and van Soest, 2001; Esty, 2001; Dasgupta et al., 2002; Harbaugh et al., 2002; Khanna, 2002; Lieb, 2002; Lindmark, 2002; Stern, 2002; Kelly, 2003; and Millimet et al., 2003). These studies have shown that there is no single relationship between environmental pollution and per capita income that fits all types of pollutants, regions, and time periods.

An important criticism of the empirical studies is that they yield little insight into the mechanisms of the inverted U-shaped relationship. At best, time trend variables have been taken into account to test for developments unrelated to income (see, for example, Hilton and Levinson, 1998). This trend may reflect technological progress resulting in lower pollution intensities. However, time trends capture several other factors, such as rising relative energy prices, resulting in substitution away from energy (Agras and Chapman, 1999). To obtain convincing statistical evidence of technology improvements, explicit indexing of a technology variable, which would capture the technological and productivity progress factors, is necessary. In their review of the

EKC literature, Stern (1998) and Dasgupta et al. (2002) noted the importance of understanding technological progress.

Andreoni and Levinson (2001) provided a theoretical explanation of the EKC, assuming economies of scale in pollution control. As economies become larger, abating the marginal unit of pollution becomes less costly and, therefore, larger economies abate more than do small ones. The object of this paper is to test this "increasing returns to abatement" hypothesis using US state-level data on pesticides. The focus on pesticides is important because, although pesticides enhance crop yields, a byproduct of their application is the contamination of surface water and groundwater. The annual loss of soil from water erosion, for example, is estimated to be approximately 1.14 billion tons per year (US Department of Agriculture, 2003). To my knowledge, there is no prior study testing the EKC in the case of pesticide use, although there are abundant studies of air and water pollution, deforestation, biodiversity conservation, and indicators of environmental amenity.

In this study, four environmental degradation indexes are used: the risk to human health from exposure to pesticide runoff; the risk to human health from exposure to pesticide leaching; the risk to fish life from exposure to pesticide runoff; and the risk to fish life from exposure to pesticide leaching. In addition, the paper combines the four indexes to construct an index of total environmental degradation from pesticides.

This study tests the hypothesis that there are increasing returns to the abatement of pollution from controlling the abatement technology level. I test this hypothesis by controlling environmental technology factors using a refined empirical method called Data Envelopment Analysis (DEA). DEA is the mathematical programming technique applied for the computation of productivity improvement (see, for example, Charnes et al., 1978; Färe et al., 1994). DEA estimates the relative efficiency of production units, identifies best practice frontiers, and provides various measures of changes in productivity over time. The combination of inputs in DEA is allowed to vary along an efficient frontier rather than the fixed coefficient production functions.

This study analyzes the environmental risk resulting from pesticide use in US agriculture using panel data for 48 states from 1970 to 1997. The issue is significant considering the importance of environmental and food safety issues (see Shortle and Abler, 2001, for a comprehensive review of agriculture and the environment). I am interested in an interstate comparative analysis because environmental regulations vary between states. Where the national technical guidance is inadequate, each individual state must develop its own management plan and each has some freedom to choose its own environmental policy with respect to pesticides given the basic setup of the federal environmental policy. As society's concern with environmental issues increases, there is a growing emphasis on improving environmental quality in farming. The actual implementations of the state policies are strongly influenced by the state-level strategies. Changes in the state-level decisions have been affected by changes in technology, the political environment, and public beliefs and preferences. If the above changes are associated with a certain average income level in the state, we can expect a relationship between a state's income level and the environmental risk, although the site-specific climate, environment, and amount or type of agriculture also cause environmental risk to vary across states.

Contrary to the EKC literature, which involves cross-country comparisons, I undertake an interstate comparison because such data are more reliable for the US than the country-level pesticide data, which are available from the Food and Agriculture Organization (FAO). Finally, using state-level data may make it safer to assume that all cross-sections adhere to the same EKC, i.e., it may not be reasonable to impose isomorphic EKCs if cross-sections vary in terms of resource endowments and infrastructure (see Unruh and Moomaw, 1998).

The paper is structured as follows. Section 2 provides a review of the literature. Section 3 describes the data and Section 4 discusses the research methods. Section 5 presents the econometric results, whereas Section 6 presents a summary and concluding remarks.

2. Data

In this study, I use state-by-year panel data (covering 48 states for the period 1970–1997) on environmental degradation (human and fish risks from leaching and runoff), real GSP, abatement efforts, the environmental productivity index, capital, intermediate inputs, and labor. Note that Alaska and Hawaii are excluded because no data are available for these states. The environmental productivity index, *Env.Tech*, is estimated from state-by-year panel data for multiple inputs and outputs including environmental variables. State-level input and output data for the 48 states are available from the USDA (Ball et al., 2001b). Outputs of crops and livestock are defined as gross production leaving the farm, as opposed to real value added. Inputs are capital, labor, and intermediate inputs. Intermediate inputs include agricultural chemicals (such as fertilizers and pesticides), petroleum fuels, natural gas, electricity, and other purchased inputs

The stringency of environmental regulation increases over time for this study. I focus on pesticide-related risks because of their importance (Ruttan, 2002). The environmental degradations are indicators of risk to humans and fish from exposure to agricultural pesticides (see Kellogg et al., 2000, for a detailed discussion of the construction of the data). This study analyzes several different risks because each risk varies greatly depending on the relevant pesticide's exposure, inherent toxicity, and hazard. The potential risk is complex and changes over space and time. Patterns of risk are driven by many factors, which include agronomic practices, economic factors, the introduction of effective nonchemical controls and new cost-effective pesticides, pest population changes, regulations, shifts in crop acreage, voluntary changes to minimize environmental/residue concerns, and the weather.

The assessment of risk is based on the extent to which the concentration of a specific pesticide exceeds each water quality threshold level. For each of around 200 pesticides applied to twelve crops—barley, corn, cotton, oats, peanuts, potatoes, rice, sugarbeets, sorghum, soybeans, tobacco, and wheat—Kellogg et al. (2000) used computer simulations in each of about 4,700 resource polygons representing the intersections of 48 states. An indicator of risk is constructed using the concentration threshold ratio when the concentration of a specific pesticide exceeds the threshold. Exposure to pesticides that leach is particularly important during low-flow conditions when most surface water originates from groundwater recharge. Hereafter, I use the following notation in units of millions of TEUs: *HR* = risk to human health from exposure to pesticide runoff; *HL* = risk to human health from exposure to pesticide leaching; *FR* = risk to fish life from exposure to pesticide runoff; and *FL* = risk to fish life from exposure to pesticide leaching. In addition, I take the summation of all four environmental degradation measures as an additional variable, named *Total*. The data show that the larger the scale, the higher is the risk to the environment. The state-level data on total research and development expenditure for water-related pollution abatement strategies are available from the Current Research Information System (CRIS) in the USDA.

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[12] Ball et al. (2001a) analyzed productivity from 1972 to 1993 using environmental variables. However, their estimates did not include the pollution abatement effort (i.e., environmental inputs) on the input side. Including environmental output and excluding environmental inputs in productivity analysis provides misleading results. For

4. Econometric methods

This study estimates a quadratic and a cubic EKC for US agriculture in 48 states from 1970 to 1997. The usual approach when facing heteroskedasticity of unknown form is to use the Generalized Method of Moments (GMM), introduced by Hansen (1982). GMM makes use of orthogonality conditions to allow for efficient estimation in the presence of heteroskedasticity of unknown form (see Mátyás, 1999). Three parametric approaches are used in this study. The first approach is a simple cubic specification that is frequently used in the literature, but my treatment is original because my pesticide risk data have not been used previously in the EKC literature. Then, the second model specification is given by,

$$Y_{it} = \alpha_0 + \alpha_1 GSP_{it} + \alpha_2 GSP_{it}^{2} + \alpha_3 Env.Tech_{it} + \alpha_4 Abate_{it} + \sum \mu_i D_i + \sum \eta_t D_t + \varepsilon_{it}, \quad (1)$$

where Y is the agricultural environmental degradation for state i and year t, GSP is the real gross state product, *Env.Tech* is the productivity progress level of environmental technologies, *Abate* is the pollution abatement effort, D_i is a dummy variable for state i, and D_t is a dummy variable for year t. I expect the dummy variables to capture state-specific factors such as geography, policy, trade, and population.

Technology and skills have been important elements in the theoretical and empirical literature on the determinants of pollution. In this study, my specification allows for technological differences over states and years. As I would like to look at the abatement level while holding the technological progress level constant, this specification includes the productivity progress level of environmental technologies in the explanatory variables, as well as the abatement level. I update the results of Managi and Karemera (2005), who estimated

Env.Tech using DEA.[2] DEA is applied for the computation of productivity change (see, for example, Charnes et al., 1978; Färe et al., 1994; Chung et al., 1997). The DEA estimates the relative efficiency of production units, identifies best practice frontiers, and provides various measures of changes in productivity over time. *Env.Tech* is estimated from two Total Factor Productivity (TFP) estimates: (i) productivity of market output (i.e., agricultural production), denoted by TFP_{Market}; and (ii) the sum of the productivity of nonmarket output (i.e., the reduction in environmental risks) plus market output, denoted by TFP_{Total}, following Managi et al. (2005). Note that DEA can handle multi-output/multi-input analysis. TFP_{Market} includes the usual production inputs and outputs, and TFP_{Total} includes environmental degradation and abatements effort, as well as production inputs/outputs. Given the input level, an increase in output raises the usual productivity, TFP_{Market}. Holding inputs and environmental output constant, an increase in good output raises TFP_{Total}. Furthermore, holding inputs and good output constant, a decrease in the environmental output raises TFP_{Total}. Thus, the residual effects of two factors explain the productivity resulting from changes in technology for the nonmarket goods (environmental degradation). These are given by,

$$Env.Tech = TFP_{Total} / TFP_{Market}, \tag{2}$$

where an increase in *Env.Tech* implies an improvement in abatement productivity, which might consist of either a greater reduction of environmental degradation given the same level of abatement effort, or a reduction of abatement efforts given the same level of environmental degradation level, or both. Thus, I expect a negative sign in *Env.Tech*, indicating that improvements in the environmental productivity or the management system have reduced environmental degradations. Note, both TFP_{Total} and TFP_{Market} are estimated each year for each state.

I expect a negative sign for the abatement effort variable, *Abate*, because an increase in the pollution abatement effort reduces the environmental degradation, holding all else constant. The next specification includes the quadratic term of the abatement effort to test the increasing returns, as follows.

$$Y_{it} = \beta_0 + \beta_1 GSP_{it} + \beta_2 GSP_{it}^{\ 2} + \beta_3 Env.Tech_{it} + \beta_4 Abate_{it} + \beta_5 Abate_{it}^{\ 2} + \sum \gamma_i D_i + \sum \lambda_t D_t + \varepsilon_{it} \quad . \qquad (3)$$

Finally, the same specifications of equations (2) and (3), without the environmental technology variable, are estimated to determine the correlation between the *Env.Tech* and the *Abate* variables.

A statistically significant negative sign on the quadratic term of abatement implies the existence of increasing returns to pollution abatements. In contrast, a significant positive sign on the quadratic term of abatement implies the existence of decreasing returns to abatement. An insignificant sign implies that I have not found any significant evidence of returns to scale. If the quadratic term of GSP is significant with a negative sign in (1) and insignificant in (3), and if the quadratic term of *Abate* is significant with a negative sign, this implies that the inverted U-shaped relationship of the EKC is explained by increasing or decreasing returns to abating pollution.

5. Results

Table 1 reports the results of estimating Equation (1). Using J statistics, I am not able to reject the hypothesis that all instruments satisfy orthogonality conditions. I find a statistically significant relationship between state patterns of environmental degradation and income levels, environmental productivity, and abatement efforts. All results show that the EKC has an inverted U-shape. The environmental technology variable shows a negative sign except for *HR*, where *Total*, *HL*, *FR*, and *FL* are statistically significant. The reason why the environmental technology variable of *HR* is not statistically significant might be related to the high turning point of the EKC pattern, i.e., it is difficult to reduce *HR*. This is consistent with the idea that farmers do not have an incentive to address human risk from pesticide runoff (*HR*) because there are no inexpensive remediation methods available, nor is there any government assistance to cover the costs. The abatement effort variable shows a negative sign except for *HR* where *Total*, *HR*, *FR*, and *FL* are statistically significant. The results of *Total* are similar to those for the runoff risks (*HR*, *FR*) because the leaching risks (*HL*, *FL*) add little to the total, being much smaller than the runoff risks although they are not significant (see Kellogg et al., 2000, for a detailed quantitative comparison). Overall, the results support the argument that productivity improvements in environmental technologies and increases in abatement efforts reduce environmental degradation, as expected.

I examine the stationarity of the residuals using the unit root tests of Im et al. (2003). In all of the specifications, I am able to reject the null hypothesis of a unit root in the residuals.

Next, I add the quadratic term of abatement effort as in Equation (3). The estimated results are shown in Table 2. The J statistics show that I am not able to reject the hypothesis that all instruments satisfy orthogonality conditions. The estimates of the quadratic term of GSP are not significant, except for *HL*. Thus, for *Total*, *HR*, *FR*, and *FL*, GSP is positively correlated with the pollution level (i.e., only the linear GSP variable terms are statistically significant), which state increases in income increase the environmental degradation. The significance level and the magnitude of coefficients for environmental technology in Table 2 are similar to those of Table 1.

Generally, an improvement in environmental technology and managements system, i.e., *Env. Tech*, reduces the environmental degradation.

All of the estimates of the quadratic term of the abatement effort show negative signs and all are significant at the 1% level. Note, however, that the linear abatement term for *HL* and *FL* is positive and statistically significant. In these cases, it is possible that an increased abatement cost is associated with an increasing rather than a decreasing pesticide risk. The estimated turning points for the abatement and pesticide risk relationship for *Total*, *HR*, *HL*, *FR*, and *FL* are –0.67, –0.29, 0.06, 1.33, and 0.12, respectively. The minimum risk values for the above five indexes are 0.18, 0.02, 0.001, 0.01, 0.001, respectively, and their average risk values are 2992.37, 2002.33, 49.75, 2887.46, and 22.20, respectively. As some turning points are larger than the minimum risk value, there are cases where increased abatement cost is associated with an increasing pesticide risk. However, it should be noted that all turning points are much smaller than the average values. Thus, the result that increased abatement cost is associated with a decreasing pesticide risk remains valid for most of the risk data. Overall, I support my hypothesis of increasing returns to pollution abatements.

Especially for *Total*, *HR*, *FR*, and *FL*, the quadratic terms of GSP are no longer significant and those of abatement are significant. This implies that increasing returns to abating pollution explains the inverted U-shaped relation of the EKC with greater statistical significance than does the income level. Thus, the driving force for reducing pesticide risk in US agriculture is the increase in pollution abatement rather than the increase in income.

In this study, I show that increasing returns to pollution abatement play an important role in determining the pollution level over the period of the study. In addition, the environmental productivity level plays an important role. Thus, in support of Andreoni and Levinson (2001), an important implication of this research is that explanations regarding abatement technology are central to understanding the phenomenon of the EKC. I examine the stationarity of the residuals using the unit root tests of Im et al. (2003). In all of the specifications, I am able to reject the null hypothesis of a unit root in the residuals. In addition, the Sargan test of overidentifying restrictions provides a p-value of 0.24 for Table 5, implying that the instruments used in this estimation are valid. The same conclusions are confirmed in all other specifications.

6. Conclusion and discussion

Theory has played a limited role in the development of the EKC literature (Copeland and Taylor, 2004), which has created difficulties in interpreting the empirical inverted U-shaped curve. Andreoni and Levinson (2001) provided a simple explanation for the EKC: pollution abatement efficiency might increase as the abatement effort rises. The efficiency increases make abatement less expensive and, thus, pollution can decrease even if environmental policies are stagnant. Thus, increasing returns to abating pollution might exist and the EKC could be explained by this relationship. In this framework, the inverted U-shaped EKC does not require any complicated political-economy models of collective decision-making, externalities, and economic growth. One implication of Andreoni and Levinson's study is that EKCs can exist whether policies are socially efficient or inefficient because of increasing returns to scale.

This study tested the increasing returns to pollution abatement in the EKC framework. It analyzed the environmental risk in US agriculture, using data on a panel of 48 states for 1970–1997. Although Andreoni and Levinson (2001) assumed no change in pollution policy, several environmental regulations have been implemented in US agriculture. Thus, rather than determining whether environmental policy is required, this test aimed to understand the impact of abatement on the pollution level. Contamination by pesticides is potentially carcinogenic. Considering the importance of the environmental and food safety issue, detecting the relationship between abatement and agricultural environmental risk is important. I utilized a dataset involving four environmental risks: the risk to human health from exposure to pesticide runoff; the risk to human health from exposure to pesticide leaching; the risk to fish life from exposure to pesticide runoff; and the risk to fish life from exposure to pesticide leaching. My estimates for US agriculture for the period 1970–1997 support the hypothesis of increasing returns to abatement.

In the existing literature, time trend variables have been taken into account to test for productivity or technology level (see, for example, Hilton and Levinson, 1998). However, the time trend may capture any effects changing over time, such as changes in relative energy prices (Agras and Chapman, 1999). Explicit indexing of a technology variable is necessary to capture the productivity factors. This study employed DEA and illustrated the important role played by the environmental productivity level, in addition to abatement efforts.

The numerical results have to be interpreted with care because inverted U-shaped relationships might become N-shaped curves in the long run. That is, they may initially exhibit the same pattern as the inverted U-shaped curve, but beyond a certain income level, return to exhibiting a positive relationship between environmental pressure and income (Pezzey, 1989; Opschoor, 1990; de Bruyn et al., 1998). Thus, delinking might be considered a temporary phenomenon. Opschoor (1990), for example, argued that once technological advances in resource use or abatement opportunities have been exhausted, or have become too expensive, further income growth will result in an increase of environmental degradation. In the same way, the evidence of increasing returns to abatement might be short-run results. In the long run, if the environmental technology level remains constant, scale economy effects might be exhausted and change to decreasing returns to abatement. Further evidence of technology is required to answer this question.

The relationship between agriculture and the environment is also complex, depending on such location-specific factors as the assimilative capacity of the natural environment, which often have not been fully explored scientifically. Moreover, the pressures on the environment from changes in agricultural production tend to differ according to the state-specific environmental regulations in place (see Shortle and Abler, 2001, for a comprehensive review). Hence, any estimate of prospective environmental impacts from agriculture is subject to considerable risk. Nevertheless, deriving quantitative estimates of the likely environmental impacts of agricultural pollution abatement might help to focus and advance the policy debate.

Table 1. GMM Parameter Estimates (Equation 1): Base Model

Dependent variable	Total	HR: Human Risk Pesticide Runoff	HL: Human Risk Pesticide Leaching	FR: Fish Risk Pesticide Runoff	FL: Fish Risk Pesticide Leaching
Gross State Product	88.773 ***	50.317 ***	1.406 ***	38.428 ***	0.454 ***
	(5.74)	(6.43)	(9.16)	(5.44)	(6.00)
(Gross State Product)^2	–31.579 ***	–14.638 ***	–0.553 ***	–16.680 ***	–0.196 ***
	(–4.69)	(–4.25)	(–6.90)	(–4.68)	(–5.23)
Abatement Effort	–75.326 **	–4.539	–2.308 ***	–76.449 ***	–0.972 ***
	(–2.28)	(1.16)	(–6.99)	(–3.76)	(–4.95)
Environmental Tech.	–27.430 *	–2.492	– 0.909 ***	–42.795 ***	–0.648 ***
	(–2.11)	(–1.18)	(–3.69)	(–2.76)	(–4.82)
Constant	90.094	12.854	0.977	74.385	0.705
J-statistic (*p-value*)	*0.2426*	*0.1866*	*0.2378*	*0.2250*	*0.1763*
Unit root test	–2.545	–2.344	–2.453	–2.389	–2.651
t-value	Reject	Reject	Reject	Reject	Reject
Time period	1970–97	1970–97	1970–97	1970–97	1970–97

Note: *** Significant at 1 %, ** Significant at 5 %, * Significant at 10 %. t statistics are in parentheses. Coefficients of dummy variables are estimated but not reported in this table.

Table 2. GMM Parameter Estimates (Equation 3): Test of Increasing Returns to Abating

Dependent variable	Total	HR: Human Risk Pesticide Runoff	HL: Human Risk Pesticide Leaching	FR: Fish Risk Pesticide Runoff	FL: Fish Risk Pesticide Leaching
Gross State Product	90.182 ***	33.951 ***	1.295 ***	52.635 ***	0.249 ***
	(4.60)	(3.32)	(6.92)	(5.32)	(2.63)
(Gross State Product)^2	–33.520	–3.639	–0.487 ***	–25.751	–0.097
	(–1.06)	(–0.68)	(–4.41)	(–0.58)	(–1.03)
Abatement Effort	– 68.172	–82.292	3.072 ***	13.488	2.003 ***
	(–1.11)	(–0.65)	(5.32)	(0.36)	(5.80)
(Abatement Effort)^2	–90.867 ***	–47.738 ***	–0.349 ***	–36.088 ***	–0.493 ***
	(–3.07)	(–3.14)	(–1.26)	(–3.05)	(–3.37)
Environmental Tech.	–37.817 *	–2.917	–0.927 ***	–31.245 *	–0.665 ***
	(–1.74)	(0.21)	(–3.75)	(–1.91)	(–4.96)
Constant	82.092	13.389	0.934	65.682	0.700
J-statistic (*p-value*)	*0.2419*	*0.1836*	*0.2514*	*0.2196*	*0.1787*
Unit root test	–2.645	–2.538	–2.634	–2.347	–2.613
t-value	Reject	Reject	Reject	Reject	Reject
Time period	1970–97	1970–97	1970–97	1970–97	1970–97

Note: *** Significant at 1 %, ** Significant at 5 %, * Significant at 10 %. t statistics are in parentheses. Coefficients of dummy variables are estimated but not reported in this table.