The Contribution of Greenhouse Pollution to Productivity Growth*

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Abstract

In this paper we examine the effect of greenhouse pollution, as measured by CO2 emissions, on economic growth among a set of OECD countries during the period 1981-1998. We examine the relationship between total factor productivity (TFP) growth and pollution using a semiparametric smooth coefficient model that allow us to directly estimate the output elasticity of pollution. The results indicate that there exists a nonlinear relationship between pollution and TFP growth. The output elasticity of pollution is small with an average sample value of 0.014. In addition we find an average contribution of pollution to productivity growth of about 1 percent for the period 1981-1998.

JEL: C14, O13, O40

Key Words: TFP Growth, Greenhouse Pollution, CO_2, Semiparametric Estimation.

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1 Introduction

Natural environment and natural resources unambiguously constitute an important factor of the growth process, the shortage of which may impose a limit to growth. This limit to growth may arise either from the finite amounts of some natural resources such as raw materials, or by nature's limited ability to absorb human waste. The emphasis of the theoretical work on the effects of the environment on economic growth was given on building growth models to study how economic policy and technological change may overcome the limits to growth imposed by the extensive use of the environment and generate a positive long-run growth rate (see Bovenberg and Smulders, 1995, Pittel, 2002, and an extensive review of the literature by Brock and Taylor, 2005).

Recently more attention has been given to the growth effects of the deterioration in the quality of the environment due to increased accumulation of pollution. Pollution, which is usually modelled as a side product of the production process (see Anderson, 1987), may affect growth through two channels. If natural environment is considered to be an input into the production function, then pollution represents the use of environmental capital, implying a positive effect of pollution on growth. If environmental quality enters the production function as an input, then pollution exerts negative effects on growth by lowering the quality of natural environment. In both cases the abatement efforts of the society reduce the available resources for production and may harm growth.

In this paper we investigate the empirical relationship between pollution and economic growth using nonparametric econometric methods to uncover possible nonlinearities in the data. The empirical literature on the growth-pollution debate has mainly focused on investigating the famous environmental Kuznets curve (EKC). This voluminous literature studies the empirical relationship between real per capita income and pollution per unit of output (see List, Millimet and Stengos, 2003 and Azomahou, Lasney and Van 2006 for two recent studies that apply nonparametric methods to study this relationship). The main result of this literature is that pollution intensity initially rises with per capita income (at the early stages of economic development) but eventually falls as per capita income rises beyond some threshold level at least for the case of developed economies (see Selten, 1994, Grossman and Krueger, 1995, List and Gallet, 1999 and Stern and Common, 2001 among others). However, there is evidence that this relationship may not be robust for a number of pollutants (see Harbaugh, Levinson and Wilson, 2002 and List, Millimet and Stengos, 2003). Less attention, however, has been given to the empirical investigation of the of the role of pollution in the production process and of the effects of pollution on economic growth.

In our paper we examine the effect of pollution, as measured by CO_2 emissions, on economic growth among the advanced industrialized countries. We construct a total factor productivity (*TFP*) index of the standard inputs, capital and labour, using the methodology that was adopted in Mamuneas, Savvides and Stengos (2006). We then examine the relationship between *TFP* growth and pollution using a semiparametric smooth coefficient model that allow us to directly estimate the elasticity of pollution. The data covers the period from 1981-1998-, for a range of *OECD* countries and the results indicate that there exist a nonlinear relationship between pollution and economic growth as captured by *TFP*.

A recent study by Tzouvelekas, Vouvaki and Xepapadeas (2006) also tries to estimate the contribution of pollution to the growth of real per capita output. Our work differs from theirs in that we employ a technique that allows us to estimate a general production function without imposing any restrictions on its functional form. Following a different line of research, Chimeli and Braden (2005) try to derive a link between *TFP* and the environmental Kuznets curve. They derive a U-shaped response of environmental quality to variations in *TFP*.

The paper is organized as follows. In the next section we present the model specification and the data description. We proceed to discuss the empirical findings and in the last section we offer concluding remarks. In the appendix we present details about the econometric methodology of the smooth coefficient semiparametric model that we use and a test of linearity that we perform.

2 Methodology and Data Sources

2.1 Specification

To examine our primary goal, based on the data available we define a general production function at time t as

$$Y_t = F(X_t, E_t, t) \tag{1}$$

where Y is the total output, X is a vector of traditional inputs like physical capital, K, and labor inputs L, E is the level of pollution stock and t is a technology index measured by time trend.

The level of pollution E_t, at time t is assumed to depend on the current pollution flow and on all past accumulated pollution,

$$E_t = P_t + (1 - \phi) E_{t-1},$$

where P is the current pollution flow, ϕ is the rate of deterioration of the pollution stock $(0 \leq \phi \leq 1)$ and E_{t-1} is the past accumulated pollution. Pollution enters the production function either as an input or as a by-product of economic activity. As an input pollution represents the extractive use of natural environment (capital). In other words, the level of pollution serves as a proxy to the input of harvested environmental resources (see Bovenberg and Smulders, 1995, and Brock and Taylor, 2005). As a by-product pollution represents a negative externality in the production process through the deterioration of the quality of the environment. Polluted air, for example, may reduce labor productivity as it adversely affects the health of individual workers and polluted rivers may harm productivity in the agricultural sector.

To determine the effect of pollution in the production process we follow an approach based on Mamuneas, Savvides and Stengos (2006) who analyzed the effect of human capital of *TFP* growth. Total differentiation of (1) with respect to time and division by Y yields:

$$\hat{Y} = \hat{A} + \varepsilon_k \widehat{K} + \varepsilon_L \widehat{L} + \varepsilon_E \hat{E} \tag{2}$$

where $(\hat{\ })$ denotes a growth rate, $\hat{A} = \frac{(\partial F/\partial t)}{Y}$ is the exogenous rate of technological change and $\varepsilon_i = \frac{\partial \ln F}{\partial \ln Q_i}, (Qi = K, L, E)$ denotes output elasticity. Subtracting from both sides of equation (2) the contribution of traditional inputs to the output growth we get

$$\hat{Y} - \varepsilon_k \widehat{K} - \varepsilon_L \widehat{L} = \hat{A} + \varepsilon_E \hat{E} \tag{3}$$

Note that the left hand side of equation (3) is directly observed from the data, if we assume a perfectly competitive environment. The output elasticities of labor and physical capital are equal to the observed income shares of labor, s_L, and physical capital, s_K. Therefore we can define a *TFP* index based on the observable data which discretely approximates the left hand side of equation (3). This index allows for the contribution of each input to differ across country and time and to be dictated by the data. We define the Tornqvist index of *TFP* growth for country i in year t as follows:

$$T\hat{F}P_{it} = \hat{Y}_{it} - w_{Lit}\hat{L}_{it} - w_{Kit}\hat{K}_{it} \tag{4}$$

where $w_{Qit} = 0.5(s_{Qit} + s_{Qit-1}), (Q_i = L, K)$ are the weighted average income shares of labor and physical capital and $\hat{Q}_{it} = \ln Q_{it} - \ln Q_{it-1}, (Q = Y, L, K)$. This measure of *TFP* contains the components of output growth that can not be explained by the growth of the inputs (K, L) in equation (3).

On the right hand side of (3) the unobserved contribution of pollution to output growth is assumed to be an unknown function of the stock of pollution, i.e., $\theta(E_{it})\widehat{E}_{it}$. Note that the function θ captures the effect of pollution to productivity growth and it can be positive or negative depending on whether the productivity or the externality effect dominates. Hence, putting all together, in a discrete form equation (3) can be written as :

$$T\hat{F}P_{it} = \hat{A}_{it} + \theta(E_{it})\widehat{E}_{it} \tag{5}$$

Equation (5) can be estimated using semiparametric methods. It allows pollution accumulation to influence *TFP* growth in a nonlinear fashion. In equation above, $\hat{A}_{it}$ can be considered as a function of country and year specific dummy variables. Country specific dummies, D_i, capture idiosyncratic exogenous technological change and time specific dummies, D_t, capture procyclical behavior of *TFP* growth. The equation of interest now becomes:

$$T\hat{F}P_{it} = \alpha_0 + \sum_{i=1}^{N-1} \alpha_i D_i + \sum_{t=1}^{T-1} \alpha_t D_t + \theta(E_{it})\widehat{E}_{it} + u_{it}$$

If we let $W_{it}^T = (D_i, D_t,)$ and $V_{it} = \{E_{it}, \Omega_{it}\}$ where Ω_{it} can be any other variable included in the smooth coefficient function, the model can be written more compactly as:

$$T\hat{F}P_{it} = W_{it}^T\beta + \theta(V_{it})\widehat{E}_{it} + u_{it} \tag{6}$$

For proper estimation we assume that $E(u_{it}|W_{it}, V_{it}, \widehat{E}_{it}) = 0$.

We proceed to estimate the model of equation (6) using a smooth varying coefficient semiparametric estimator. A smooth coefficient semiparametric model is considered to be a useful and flexible specification for studying a general regression relationship with varying coefficients. It is a special form of varying coefficient models and it is based on polynomial regression, see

Fan (1992) Fan and Zhang (1999), Li *et al* (2002) and Mamuneas, Savvides and Stengos (2006), among others. A semiparametric varying coefficient model imposes no assumption on the functional form of the coefficients, and the coefficients are allowed to vary as smooth functions of other variables. Specifically, varying coefficient models are linear in the regressors but their coefficients are allowed to change smoothly with the value of other variables. In the appendix we present the mechanics of the method in more detail.

2.2 Data Sources

In order to investigate the empirical relationship between pollution and aggregate output, we collected data from the World Bank and the *OECD* databases covering a wide range of countries over the period 1981-1998. The countries chosen are based on data availability. The countries included in this analysis are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Korea, Netherlands, Norway, Portugal, Spain, Sweden, UK and USA.

The *OECD* databases provide data on *GDP*, employment and capital formation All data are in millions of Euros and the base year is 2000. Output, Y, is defined as the *GDP* in constant prices Labor input, L, is defined as the total man-hours (total number of workers times hours worked) and the share of labor, s_L directly obtained from *OECD*. The capital stock, K, was constructed by accumulating gross investment in constant prices, using the perpetual inventory method, with a depreciation rate of 4%. The share of capital input s_K is implicitly obtained as $1 - s_L$

As a proxy for pollution flow we used CO_2 emissions, obtained from the 2002 World Development Indicators. According to the World Bank definition, CO_2 (carbon dioxide) emissions (kt) are those stemming from the burning of fossil fuels and the manufacture of cement. They include contributions to the carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. CO_2 is a stable gas which is not transformed chemically in the atmosphere. However, some CO_2 is removed from the atmosphere by a natural process that includes the effect of vegetation, soils and oceans. Moreover, human activities such as reforestation, deforestation or land management may increase or decrease the amount of CO_2 removed from the atmosphere. This degree of atmospheric removal because of combined natural and human activities corresponds to a depreciation rate that is used to construct the total "stock" of accumulated pollution. The global natural CO_2 removal rate for the set of countries that we examine has been estimated to be around 60 percent for the period 1980 to 1989 and 52 percent for the 1989 to 1998 period, see IPCC, 2000. If one adds the human-induced changes in land use and forestry we derived country-specific values on the basis of CO_2 emission data provided in the web-site of the United Nations Framework Convention on Climate Change (*UNFCCC*)[1]. As part of their obligation, countries report to the *UNFCCC* their annual emissions of greenhouse gases, with data currently spanning the period 1990-2004. For all countries in our sample, emissions are provided with and without taking into account CO_2 removal resulting from direct human-induced Land Use, Land Use Change and Forestry (*LULUCF*). The ratio of emissions with *LULUCF* over emissions without *LULUCF* gives the rate of CO_2 removal because of human activities. The overall removal rate (depreciation rate) from both human activities and natural processes for the countries in our sample over the period that we examine is around seventy percent which is what we use in our estimation. to construct the total "stock" of accumulated pollution.

To express emissions in concentration terms, which is a more appropriate measure of pollution (see Brock and Taylor, 2005), we divide the stock of emissions with the surface of each country so that our pollution stock

[1] See http://unfccc.int/ghg_emissions_data/predifined_qeuries/items/3814.php

variable, E, measures CO_2 emissions in kilotons per square kilometer. This is a measure of pollution intensity and it is closely related to pollution concentration which is emissions measured as milligrams per cubic meter. The implication of this new pollution intensity concentration variable for our empirical specification is that the damage caused by CO_2 emission to the environment depends on the size of the natural environment[2].

3 Empirical Findings

We estimate the model of equation (6) using a smooth coefficient semiparametric estimator. In particular we are interested in the unknown coefficient function $\theta(E)$. The results are presented in Figure 1. The effect of pollution on growth is positive. This implies that the productivity effect dominates the negative externality effect. In addition this effect is nonlinear. It is nearly constant up to a certain level of pollution intensity and then it appears to accelerate at higher levels. The presence of such a threshold effect is consistent with the presence of newer pollution abatement technologies "cleaner technologies" that kick in at higher levels of pollution and are responsible for increasing productivity gains. These productivity gains might also come from reduction of negative pollution externalities due to abetment. It is interesting to note that the threshold that we obtain in Figure 1 can be also given an *EKC* interpretation as it would correspond to the peak of the inverted U relationship. This is consistent for instance, with the evidence found in Stern and Common, 2001, for another pollutant, sulfur,

[2] In the empirics of economic growth it is customary to express variables in a per capita basis. However, in the environmental engineering literature it is the concentration of pollution that is of interest. In our case, the elasticity of pollution intensity that we estimate is the same as that of pollution concentration and as such it is the appropriate concept to use. Another possible standardization, division by total GDP is likely to introduce endogeneity issues.

for the group of developed economies similar to the ones we examine.

We proceed to test the specification of our model. First we test that the model that generated the data in the graphs of Figure 1 is linear. In the appendix we present the mechanics of the linearity test that we employ. We strongly reject the null hypothesis of linearity with a zero p-value for the test statistic that we obtained.

Next, we proceed to investigate the robustness of our findings. We first check for possible endogeneity of the pollution variable. We instrument it by past values of output and input quantities. We tried different sets of past values but the results were fairly robust and the shapes of the graph in Figure 1 was left intact, irrespective of the different instruments we used.

Finally we test the robustness of our model by examine the presence of a possible misspecification bias due to the omission of other important effects. The recent literature examining the effect of human capital on economic growth, see Kalaitzidakis *et al* (2001) and Mamuneas, Savvides and Stengos (2006) suggests that there exists a nonlinear relationship between human capital and economic growth. We proceed to examine whether such a nonlinear relationship between human capital and growth still persists in the presence of pollution effects. To put it differently, we would like to see whether the nonlinearity that we found in the pollution and productivity growth relationship was the result of an omitted human capital effect. We augment the analysis by including human capital, H, in the nonlinear part of the model with a second smooth coefficient function.[3] When estimating the smooth coefficient semiparametric model we obtain estimates of $\theta_1(E,H)$ and $\theta_2(E,H)$, the output elasticities of pollution and human capital respectively as functions of both pollution and the level of human capital.[4] We find

[3]The model in this case is given by $T\hat{F}P_{it} = W_{it}^T\beta + \theta_1(E,H)\widehat{E}_{it} + \theta_2(E,H)\widehat{H}_{it} + u_{it}$, where H is the human capital stock.

[4]The human capital stock data are obtained and updated from Vikram and Dhareshwar (1993). For a full description of their methodology see Vikram, Swanson and Dubey

that the nonlinear effect of pollution evaluated at the mean level of human capital is very robust. Overall, we find that pollution has a positive but nonlinear effect on productivity, an effect which depends on its level in each country under investigation. Similarly, we find that the output elasticities of human capital evaluated at the mean value of pollution are similar to the one found previously in the literature, see Mamuneas, Savvides and Stengos (2006)[5].

To examine the effect per country we have calculated the average output elasticity of pollution per country and the results are presented in the first column of Table 1. The results indicate that the average elasticity of pollution for all countries is 0.0136. This implies that 1% increase of pollution increases on average output by only 0.014%. In addition it is clear from the table that the average elasticity of pollution per country varies according to the country's pollution levels. It is interesting to note that countries like Belgium, Korea and Netherlands have output elasticities above the values of the other countries of the sample. The second column of Table 1 provides the average percent contribution of pollution growth on *TFP* growth. The results vary by country, depending on the output elasticity of pollution and the pollution growth rate. These results indicate that the effect of pollution on *TFP* growth and hence output growth is significant but rather small for most countries of the sample (the average is less than 2%) with certain exceptions for given countries. For the period of consideration (1981-1998) pollution contributes positively to *TFP* growth about 17% in Korea,

(1995). Their data covers the period 1950 to 1990 and they define human capital stock, H, as total mean years education. We use extrapolation to update the human capital stock up to 1998. For the update of the data we also take into consideration the human capital stock constructed by Barro and Lee (2001). However, we can not directly use the Barro and Lee data for our analysis since their human capital data are calculated in 5 year intervals.

[5] The results of the analysis with the inclusion of human capital as an additional input are not reported and are available from the authors.

9% in Netherlands, and 7% in Denmark for example, while it contributes negatively for countries like Finland -6%, and Spain -5%.

4 Conclusion

In this paper we have studied the effect of pollution, as measured by CO_2 emissions in kilotons per square kilometer, on economic growth among the advanced industrialized countries. We construct a *TFP* growth index by subtracting from the output growth the weighted growth of physical capital and labor inputs, using the observed income shares of physical capital and labor as weights. The *TFP* index based on the observable data allows for he contribution of each input to differ across country and time and to be dictated by the data We then examine the relationship between *TFP* growth and pollution using a semiparametric smooth coefficient model that allow us to directly estimate the elasticity of pollution.

Our results indicate that there exists a robust nonlinear relationship between pollution and economic growth as captured by *TFP* growth. We find that the pollution effect varies depending on a country's pollution level. On average pollution elasticities vary among the contributes with an average pollution elasticity (all countries) of 0.014. In addition pollution contributes on average about 1.2% to productivity growth in the countries of our sample for the period 1981-1998.

References

Ahmad, I., Leelahanon, S., Li, Q., 2005. Efficient estimation of a semiparametric partially varying linear model. *Annals of Statistics*, forthcoming.

Azomahou, T., Laisney, F., Nguyen Van, P., 2006. Economic development and CO_2 emissions: a nonparametric panel approach. *Journal of Public Economics* 90, 1347-1363.

Anderson, C.L., 1987. The production process: Inputs and wastes. *Journal of Environmental Economics and Management* 14, 1-12.

Barro, R.J., Lee, J.W., 2001. International data on educational attainment: updates and implications. CID Working Paper No. 42.

Bovenberg, A.L., Smulders, S., 1995. Environmental quality and pollution-augmenting technological change in a two-sector endogenous growth model. *Journal of Public Econeconomics* 57, 369-391.

Brock, W., Taylor, M.S., 2005. Economic growth and the environment: a review of theory and empirics. In:Aghion, P., Durlauf, S. (Eds.), *Handbook of Economic Growth II.* Chap. 28, Elsevier, 1749-1821.

Chimeli, A.B., Braden, J.B., 2005. Total factor productivity and the environmental Kuznets curve. *Journal of Environmental Economics and Management*49, 366-380.

Fan, J., 1992. Design-adaptive nonparametric regression. *Journal of the American Statistical Association* 87, 998-1004.

Fan, J., Zhang, W., 1999. Statistical estimation in varying-coefficient models. *Annals of Statistics* 27, 1491-1518.

Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. *Quarterly Journal of Economics* 110, 353-377.

Harbaugh, T.,W., Levinson A., Wilson, D.,M., 2002. Reexamining teh empirical evidence for an environmental Kuznets curve. *Review of. Economics and Statistics* 84, 541-551.

Hoover, D.R., Rice, C., Wu, C.O and L.P Yang, 1998 Nonparametric Smoothing Estimates of Time-Varying Coefficient Models with Longtitudinal Data, *Biometrica, 85, 809-822.*

IPCC, 2000, IPCC Special report on Land Use Change and Forestry-Summary for Policymakers. Intergovernmental Panel on Climate Change, Geneva, *http://www.ipcc.ch/pub/srlulucf-e.pdf.*

Kalaitzidakis, P., Mamuneas, T.P., Stengos, T., 2001. Measures of human capital and nonlinearities in economic growth. *Journal of Economic Growth* 6, 229-254.

Li, Q., Huang, C., Li, D., Fu, T., 2002. Semiparametric smooth coefficient models. *Journal of Business Economics and Statistic*s 20, 412-422.

Li, Q. and S. Wang, 1998, "A Simple Consistent Bootstrap Test for a Parametric Regression Functional Form," *Journal of Econometrics, 87, 145-165.*

List, J.A., Gallet, C.A., 1999. The environmental Kuznets curve: Does one size fit all? *Ecological Econ.* 31, 409-423.

List, J.A., Millimet, D., Stengos, T., 2003. The environmental Kuznets curve: Real progress or misspecified models? *Review of. Economics and Statistic*s 85, 1038-1047.

Mamuneas, T.P., Savvides, A., Stengos, T., 2006. Economic development and the return to human capital: a smooth coefficient semiparametric approach. *Journal of Applied Econometrics* 21, 111-132.

Pittel, K., 2002. *Sustainability and Economic Growth*. Edward Elgar.

Selten, T.M., 1994. Environmental quality and development: Is there a Kuznets curve for air pollution emission? *Journal of Environmental Economics and Management* 27, 147-162.

Stern, D., Common M.S., 2001. Is there an Environmental Kuznets curve for sulfur? *Journal of Environmental Economics and Management* 41, 162-178.

Tzouvelekas, E., Vouvaki, D, Xepapadeas, A., 2006. Total factor productivity and the environment: a case for green growth accounting. Mimeo, University of Crete.

Vikram, N., Dhareshwar, A., 1993. A new database on physical capital stock: sources, methodology and results. *Rivista de Analisis Economico* 8, 37-59.

Vikram, N., Swanson, E., Dubey, A., 1995. A new database on human capital stock in developing and industrial countries: sources, methodology and results. *Journal of Development Economics* 46, 379-401.

Zhang, W., Lee, S.-Y., Song, X., 2002. Local polynomial fitting in semivarying coefficient model. *Journal of Multivariate Analysis* 82, 166-188.

Zheng, J.X., 1996, "A Consistent Test of Functional Form via Nonparametric Estimation Techniques," *Journal of Econometrics, 75, 263-289.*

5 Appendix

5.1 Econometric Estimation: A Smooth Coefficient Semiparametric Approach

A semiparametric varying coefficient model imposes no assumption on the functional form of the coefficients, and the coefficients are allowed to vary as smooth functions of other variables. Specifically, varying coefficient models are linear in the regressors but their coefficients are allowed to change smoothly with the value of other variables. One way of estimating the coefficient functions is by using a local least squares method with a kernel weight function. A semiparametric smooth coefficient model is given by:

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + u_i \tag{A1}$$

where y_i denotes the dependent variable (the TFP index as discussed earlier), x_i denotes a $p \times 1$ vector of variables of interest (in the case of equation (6), $\widehat{E}_{it}$ and $\hat{H}_{it}$), z_i denotes a $q \times 1$ vector of other exogenous variables (the $V_{it} = \{E_{it}, \Omega_{it}\}$ from equation (5) above) and $\beta(z_i)$ is a vector of unspecified smooth functions of z_i ($\theta(.)$ in equation (6)). To simplify the exposition, we ignore the partially linear nature of equation (6), by suppressing for now the vector of the $w\prime s$. Based on Li et. al. (2002), the above semiparametric model has the advantage that it allows more flexibility in functional form than a parametric linear model or a semiparametric partially linear specification. Furthermore, the sample size required to obtain a reliable semiparametric estimation is not as large as that required for estimating a fully nonparametric model. It should be noted that when the dimension of z_i is greater than one, this model also suffers from the "curse of dimensionality", although to a lesser extent than a purely nonparametric model where both z_i and x_i enter nonparametrically. Fan and Zhang (1999), suggest that the appeal of the varying coefficient model is that by allowing coefficients to depend on other variables, the modelling bias can significantly be reduced and the curse of dimensionality can be avoided. Equation (6) above can be rewritten as

$$y_i = \alpha(z_i) + x_i^T \beta(z_i) + \varepsilon_i = (1, x_i^T) \begin{pmatrix} \alpha(z_i) \\ \beta(z_i) \end{pmatrix} + \varepsilon_i \tag{A2}$$

$$y_i = X_i^T \delta(z_i) + \varepsilon_i$$

where $\delta(z_i) = (\alpha(z_i), \beta(z_i)^T)^T$ is a smooth but unknown function of z. One can estimate $\delta(z)$ using a local least squares approach, where

$$\widehat{\delta}(z) = [(nh^q)^{-1} \sum_{j=1}^{n} X_j X_j^T K(\frac{z_j - z}{h})]^{-1} \{(nh^q)^{-1} \sum_{j=1}^{n} X_j y_j K(\frac{z_j - z}{h})\}$$

$$= [D_n(z)]^{-1} A_n(z)$$

and$D_n(z) = (nh^q)^{-1} \sum_{j=1}^{n} X_j X_j^T K,\ A_n(z) = (nh^q)^{-1} \sum_{j=1}^{n} X_j y_j K,\ K = K(\frac{z_j - z}{h})$ is a kernel function and $h = h_n$ is the smoothing parameter for sample size n. The intuition behind the above local least-squares estimator is straightforward. Let us assume that z is a scalar and $K(.)$ is a uniform kernel. In this case the expression for $\widehat{\delta}(z)$ becomes

$$\widehat{\delta}(z) = [\sum_{|z_j - z| \leq h} X_j X_j^T]^{-1} \sum_{|z_j - z| \leq h} X_j y_j$$

In this case $\widehat{\delta}(z)$ is simply a least squares estimator obtained by regressing y_j on X_j using the observations of (X_j, y_j) that their corresponding z_j is close to z ($|z_j - z| \leq h$). Since $\delta(z)$ is a smooth function of z, $|\delta(z_j) - \delta(z)|$ is small when $|z_j - z|$ is small. The condition that nh^q is large ensures that we have sufficient observations within the interval $|z_j - z| \leq h$ when $\delta(z_j)$ is close to $\delta(z)$. Therefore, under the conditions that $h \to 0$ and $nh^q \to \infty$, one can show that the local least squares regression of y_j on X_j provides a consistent estimate of $\delta(z)$. In general it can be shown that

$$\sqrt{nh^q}(\widehat{\delta}(z) - \delta(z)) \to N(0, \Omega)$$

where Ω can be consistently estimated. The estimate of Ω can be used to construct confidence bands for $\widehat{\delta}(z)$. We use a standard multivariate kernel density estimator with Gaussian kernel and cross validation to choose the bandwidth.

An interesting special case of equation (A2), is when the $w\prime s$ from equation (6) are taken into account. In that case some of the coefficients in equation (A2) are constants (independent of z). In that case, equation (A2) can be rewritten as

$$y_i = W^T\alpha + X_i^T\delta(z_i) + \varepsilon_i \tag{A3}$$

where W_i is the $i-th$ observation on a $(q \times 1)$ vector of additional regressors that enter the regression function linearly (in our case where W the country specific and time dummies $(D_i, D_t,)$. The estimation of this model requires some special treatment as the partially linear structure may allow for efficiency gains, since the linear part can be estimated at a much faster rate, namely $\sqrt{n}$.

The partially linear model in equation (A3) has been studied by Zhang *et al* (2002) and Ahmad *et al* (2005). Zhang *et al* (2002) suggest a two-step procedure where the coefficients of the linear part are estimated in the first step using polynomial fitting with an initial small bandwidth using cross validation, see Hoover *et al* (1998). In other words the approach is based on undersmoothing in the first stage. Then these estimates are averaged to yield the final first step linear part estimates which are then used to redefine the dependent variable and return to the environment of equation (A1) where local smoothers can be applied as described above.

5.2 Linearity Test

We will present below a test statistic that was used by Li *et al* (2002). In our implementation we will use a bootstrap version of this test. Let y_i

denote the dependent variable, and let x_i be $p \times 1$ and z_i be $q \times 1$ vectors of exogenous variables. Consider the following linear model

$$y_i = \alpha_0(z_i) + x_i^T \beta_0(z_i) + \varepsilon_i = (1, x_i^T) \begin{pmatrix} \alpha_0(z_i) \\ \beta_0(z_i) \end{pmatrix} + \varepsilon_i \tag{A4}$$

$$y_i = X_i^T \delta_0(z_i) + \varepsilon_i$$

where $\delta_0(z_i) = (\alpha_0(z_i), \beta_0(z_i)^T)^T$ is a smooth known function of z.For example in the context of equation (2), ignoring for the moment the presence of the $w\prime s$, we have $\alpha_0(z_i) = \alpha + z_i\theta$ and $\beta_0(z_i) = \beta$. Similarly equation (A1) captures the case of the augmented version of (2) to allow for the simple interactions of the $x\prime s$ with z, where $\alpha_0(z_i) = \alpha + z_i\theta$ and $\beta_0(z_i) = \beta_1 + \beta_2 z$.

We can test the adequacy of (A1), the H_0, against the semiparametric alternative (1) using the following test statistic.

$$\begin{aligned} \widehat{I}_n &= \frac{1}{n^2 h^q} \sum_i \sum_{j \neq i} X_i^T (y_i - X_i^T \widehat{\delta}_0(z_i)) X_j (y_j - X_j^T \widehat{\delta}_0(z_j)) K(\frac{z_j - z_i}{h}) \\ &= \frac{1}{n^2 h^q} \sum_i \sum_{j \neq i} X_i^T X_j \widehat{\varepsilon}_i \widehat{\varepsilon}_j K(\frac{z_j - z_i}{h}) \end{aligned}$$

where $\widehat{\varepsilon}_i$ denotes the residual from parametric estimation (under H_0). It can be shown that under H_0, $J_n = nh^{q/2}\widehat{I}_n/\widehat{\sigma}_0 \longrightarrow N(0,1)$, where $\widehat{\sigma}_0^2$ is a consistent estimator of the variance of $nh^{q/2}\widehat{I}_n$, see Li *et al* (2002). It can be shown that the test statistic is a consistent test for testing H_0 (equation (3)) against H_1 (equation (1)). We use a bootstrap version of the above test statistic, since bootstrapping improves the size performance of kernel based tests for functional form, see Zheng (1996) and Li and Wang (1998).

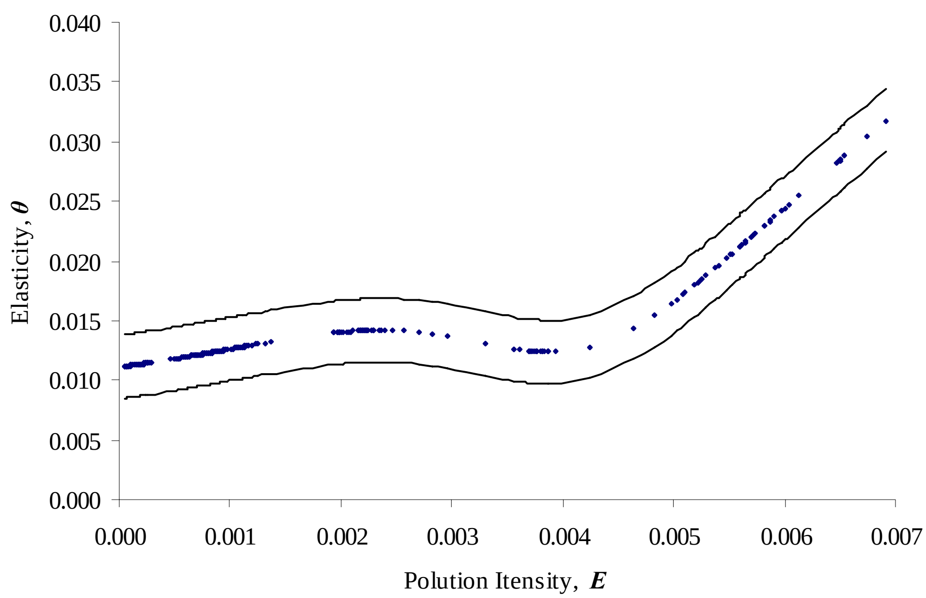

Figure 1: Polution Elasticities

Table 1: Pollution Elasticities and Contribution To *TFP* Growth
Mean Values 1981-1998 (Std. Error)

Country	**Elasticity** $\theta(E)$	**Constribution to TFP** $\frac{\theta(E)\times\widehat{E}}{\widehat{TFP}}\times 100$
Australia	0.0112	2.98
	(0.00001)	
Austria	0.0128	-0.90
	(0.00009)	
Belgium	0.0218	-0.24
	(0.00317)	
Canada	0.0112	-0.56
	(0.00001)	
Denmark	0.0141	7.41
	(0.00005)	
Finland	0.0114	-5.99
	(0.00003)	
France	0.0128	1.61
	(0.00015)	
Greece	0.0124	0.00
	(0.00022)	
Ireland	0.0121	1.00
	(0.00015)	
Italy	0.0141	-3.77
	(0.00008)	
Korea	0.0175	17.49
	(0.00637)	
Netherlands	0.0221	8.83
	(0.00432)	
Norway	0.0113	0.35
	(0.00004)	
Portugal	0.0121	-2.73
	(0.00026)	
Spain	0.0121	-4.52
	(0.00011)	
Sweden	0.0114	-1.02
	(0.00003)	
UK	0.0124	0.17
	(0.00005)	
USA	0.0123	1.72
	(0.00011)	
All Countries	0.0136	1.21
	(0.00381)	