Pollution Spillovers and U.S. state Productivity Growth

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Abstract
This paper measures the effect of pollution and pollution spillovers on the Total Factor Productivity growth among the 48 U.S. states, for the period 1977-2002. As a measure of pollution we use two air pollutants: nitrogen Oxides (NOx) and sulphur dioxide (SO2). In turn, we use two different measures of these pollutants; ambient concentration rates and emission density. We examine the relationship between TFP growth and pollution using a semiparametric smooth coefficient model that allows us to directly estimate the elasticity of pollution without imposing any restriction on the functional form of the production function. Following the same methodology, we also account for the effect of interstate pollution spillovers on state level productivity growth. The results indicate that there is a positive relationship between a state’s “own pollution” and TFP growth whereas in the case of the spillover pollution the relationship with TFP growth is negative.

\textit{JEL}: C14, O13, O40
\textit{Key Words}: TFP Growth, Pollution, Transboundary Pollution Spillovers, Semiparametric Estimation.
1. Introduction

The relationship between economic growth and environmental quality has been an object of debate for many years now. In this paper we examine two issues. First we investigate the empirical relationship between two different pollutants and economic growth. Second we extent the analysis by including transboundary pollution spillovers and investigate how the dispersion of these pollutants affects this relationship. We use nonparametric econometric techniques that allow us to directly estimate the elasticity pollution and pollution spillovers for each state and each period and to account for possible nonlinearities in the data.

A number of studies have investigated the relationship between environmental quality and economic growth. Most of the literature has focused on examining the relationship between indicators of environmental degradation (a variety pollutants such as sulphur dioxide, nitrogen oxides, carbon monoxide etc) and per capital income. This is the well know Environmental Kuznets Curve (EKC) literature. There are numerous reviews concerning the Kuznets curve literature (see Stern et al (1996), Ekins (1997), Stern (1998), de Bruyn and Heintz (1998), Stagl (1999), Dasgupta et al. (2002), Cole (2003), Stern (2004), Dinda (2004)).

The pioneering empirical work in this literature was the work of Grossman and Krueger (1993, 1995). They found that concentration rates of some pollutants (sulphur dioxide, dark matter and suspended particulates) rose at first but then fell with increases in per capita income. Various methodologies, mostly fixed and random effects models, were applied in examining the relationship between the environment and economic growth. Two recent studies apply nonparametric methods to examine this relationship (List, Millimet and Stengos (2003), Azomahou, Lasney and Van, (2006)). Most of the empirical studies following the study of Grossman and Krueger (1993, 1995) that have examined the relationship between pollution and income confirm the inverted-U relationship between pollution and income (See Selden and Song (1994), Stern and Common (2001), List and Gallet (1999), Shukla and Parikh (1992), Barbier (1997), Ansuategi et al. (1998), Tucker (1995), etc.). However the empirical evidences also
provide controversy about the validity of the EKC hypothesis (inverted-U relationship between pollution and income) mostly depending on the choice of the pollution indicators. That is the EKC hypothesis is not confirmed for all types of pollutants (see Harbaugh, Levinson and Wilson (2002), List, Millimet and Stengos (2003)). Also, in Chimeli & Braden (2005) the authors try to link Total Factor Productivity (TFP) with the Environmental Kuznets curve. They find a U-shaped response of environmental quality to variations in TFP.

Before proceeding any further it is important also to mention the work done in modeling pollution in the production processes. The inclusion of pollution in the technology underlying the production process requires first one to classify pollution either as an input or as an (another) output of the process. Those who model pollution as an input argue that since by trying to reduce pollution (abatement) involves diverting some of the traditional inputs into the abatement effort results in fewer inputs available in the production of goods. In other words they argue that by reducing pollution, output is reduced and in this sense pollution can be treated as an input into production (see, e.g., Baumol and Oates (1988), Laffont (1988), Cropper and Oates (1992), Koop (1998), Reinhard, Lovell, and Thijssen (1999) and Murty and Kumar (2002)). Another defending argument to the use of pollution as an input is that pollution represents the extractive use of natural environment. That is pollution is treated as a proxy for the use of environmental resources (see Bovenberg and Smulders (1995), Brock and Taylor (2005)).

Modelling pollution as an output captures the idea that “good” output cannot be produced unless pollution (“bad output”) is produced (see e.g., Fare, Grosskopf, Lovell, and Yaisawarng (1993), Ball, Lovell, Nehring, and Somwaru (1994), Fare and Grosskopf (1998), and Fare Grosskopf, and Weber (2006)). That is pollution is a byproduct of the production of goods. As a byproduct pollution can be considered as a negative externality in the production process in that it deteriorates the quality of the environment.

Modelling of bad outputs took various forms in the literature. Fernandez et al. (2002), model good and bad outputs separately in a stochastic frontier context. This approach
allows for the definition of two separate types of efficiency; technical efficiency which is related to the "goods" frontier, and environmental efficiency that corresponds to the "bads" frontier. Both these measures can be estimated from the data. In their paper, Fernandez, Koop and Steel (2005) use a single frontier and they measure efficiency by looking at the distance between the frontier and the observed data. They define an output aggregator equation where they differentiate good from bad outputs by introducing bad outputs in the equation with a negative power. The way they specify their output aggregator equation implies that it is not possible to produce goods without bads; this is in line with the idea that bads are unavoidable byproducts of the goods production process. A number of applied studies have used similar approaches in other industrial applications (e.g., Fare, Grosskopf and Tyteca (1996), Fare, Grosskopf and Pasurka (2001)).

In summary, pollution can affect growth in two ways. Pollution can positively affect growth because it represents the use of natural environment in the production process (positive productivity effect). On the other hand pollution can have a negative effect on growth since it also represents a negative externality in the production process through the deterioration of environmental quality. Pollution, for example can harm the health of productive agents in the economy, deteriorates natural recourses resulting in bad quality inputs or outputs (for example materials, fishing industries, agriculture crops). It also increases the cost of firms due to pollution abatement imposed via environmental regulations. In this paper we are empirically trying to determine the effect of pollution on growth.

In a recent study Tzouvekas, Vouvaki and Xepapadeas (2006) estimate the contribution of pollution to the growth of real per capita output. Their work is conceptually similar to the first task of this paper. The difference is that we estimate a general production function, without the need to impose any restriction to its functional form by using nonparametric methods.
Even though the work done in this literature is extensive, it does not account for the spatial dispersion of pollution. As far as the EKC literature, most of the models proposed do not consider how the existence of transboundary pollution spillovers-externalities affects the relationship between pollution and economic growth. Only very few papers have taken into account the spatial relationship between countries that arises from the transboundary nature of pollutants (Ansuategi (2003), Murdoch, Sandler, Sargent (1997), Stern (2000). Maddison (2006, 2007), Hauer and Runge (2000)). Most of these papers use data on sulfur dioxide emissions in a panel of European countries (Madisson (2006, 2007) uses more pollutants).

As far as we know there has been no empirical work done in investigating the effect of interstate pollution spillovers on Total Factor Productivity (TFP) growth. The contribution of this paper is to do exactly that. Also, the data set is for the U.S. states and not for European countries. In other words the goal of the paper is to explore the relationship between pollution, pollution spillovers and U.S. state productivity growth.

More precisely this paper measures the effect of pollution and pollution spillovers on the Total Factor Productivity growth among the U.S. states. As a measure of pollution we use two air pollutants: nitrogen Oxides (NOx) and sulphur dioxide (SO2). In turn, we use two different measures of these pollutants; ambient concentration rate and emission density (emissions divided by the size of a state). We construct a Total Factor Productivity (TFP) growth index of the standard inputs, capital and labor, using the methodology that was adopted in Mamuneas, Savvides and Stengos (2006). This index of TFP growth takes into account only the contribution of the “traditional” inputs (capital and labor). We then examine the relationship between TFP growth and pollution using a semiparametric smooth coefficient model that allows us to directly estimate the elasticity of pollution without imposing any restriction on the functional form of the production function. Finally, following the same methodology, we try to account for the effect of interstate
pollution spillovers on state level productivity growth. The data used cover the period from 1977-2002, for the 48 contiguous U.S. states\(^1\).

To anticipate the main findings, it seems that by ignoring interstate pollution spillovers, when we only use concentration rates as our measure of pollution the effect on TFP growth is negative but very close to zero. On the other hand when we use emissions density the effect on TFP growth is positive. Together these results and accounting for the different nature of these two measurements led us to verify the need of explicitly accounting for the effect of a state’s “own pollution” that is the pollution produced locally and stayed within a state’s boundary and the “pollution received” from other states. That is the pollution produced outside a state’s border but transported inside the state’s area (and therefore was included in the measurements of the state’s ambient concentration rates). By accounting for interstate spillovers in the analysis the results indicate that there is a positive relationship between “own pollution” and TFP growth whereas in the case of the “pollution received” the relationship with TFP growth is negative.

The paper is organized as follows. In the next section we present the model specification. In section 3 we describe the data used in the empirical part of the paper. In section 4 we discuss the empirical findings and in the last section we offer concluding remarks.

2. Methodology

We use two models, one in order to investigate the relationship between each state’s pollution and productivity growth and the second in order to re-estimate this relationship by also accounting for interstate pollution spillovers.

2.1. Specification of Model 1

In order to examine our first goal, based on the data available we define a general production function

\(^1\) When the measure of pollution is the ambient concentration rate, the sample covers only 46 U.S. states. We excluded the states of North and South Dakota due to a lot of missing values.
where $Y$ is the total output, $X$ is a vector of traditional inputs like physical capital, $K$, and labor inputs $L$, $P$ is the pollution measure. $t$ is a technology index measured by time trend.

We use three pollution measures: concentration rates, emissions per square kilometer and the stock of emissions per square kilometer. The stock of emissions at time $t$ is assumed to depend on the current pollution flow and on all past accumulated pollution,

$$P_{it} = E_{it} + (1 - \phi)P_{it-1}$$

$E_{it}$ is the current emission flow per square kilometer, $\phi$ is the rate of deterioration of the pollution stock ($0 \leq \phi \leq 1$) and $P_{it}$ is the past accumulated pollution. When $\phi=1$, $P_{it}=E_{it}$ and the pollution level depends on just the current pollution flow. For values of $0 \leq \phi < 1$, pollution is a stock and depends on past accumulated pollution levels.

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 (2.1.1) with respect to time and division by $Y$ yields:

$$\hat{Y} = \hat{A} + \epsilon_k \hat{K} + \epsilon_L \hat{L} + \epsilon_P \hat{P}$$

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

$$\hat{Y} - \epsilon_k \hat{K} - \epsilon_L \hat{L} = \hat{A} + \epsilon_P \hat{P}$$

The left hand side of equation (2.1.3) 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 (2.1.3). 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:

$$ TFP_{it} = \hat{Y}_{it} - w_{L,lt}\hat{L}_{it} - w_{K,kt}\hat{K}_{it} \tag{2.1.4} $$

where $w_{Qi} = 0.5(s_{Qi} + s_{Qi-1})$, $(Q_i = L, K)$ are the weighted average income shares of labor and physical capital and $Q_i = \ln Q_i - \ln Q_{i-1}$, $(Q = Y, L, K)$. 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 (2.1.3).

On the right hand side of (2.1.3) the unobserved contribution of pollution to output growth is assumed to be an unknown function of the stock of pollution, i.e., $\theta(P_{it})\hat{P}_{it}$. Hence, putting all together, in a discrete form equation (2.1.3) can be written as:

$$ TFP_{it} = \hat{A}_{it} + \theta(P_{it})\hat{P}_{it} \tag{2.1.5} $$

Equation (2.1.5) can be estimated using semiparametric methods. It allows pollution to influence TFP growth in a nonlinear fashion. In equation above, $\hat{A}_{it}$ can be considered as a function of state and year specific dummy variables. State 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:

$$ TFP_{it} = \alpha_0 + \sum_{i=1}^{N-1} \alpha_i D_i + \sum_{t=1}^{T-1} \alpha_i D_t + \theta(P_{it})\hat{P}_{it} + u_{it} $$

If we let $W_{it} = (D_i, D_t)$ and $V_{it} = \{P_{it}, \Omega_{it}\}$ where $\Omega_{it}$ can be any other variable included in the smooth coefficient function, the model can be written more compactly as:
For proper estimation we assume that $E(u_{it}|W_{it},V_{it},\hat{P}_{it})=0$.

We estimate the model of equation (2.1.6) using a smooth varying coefficient semiparametric estimator. The estimation approach adopted here is based on the smooth coefficient semiparametric model. It is a generalization of varying coefficients models and it is based on polynomial regression, see Fan (1992), Fan and Zhang (1999), Li et al (2002), Kourtellos (2003) and Mamuneas, Savvides and Stengos (2006) among others. A smooth coefficient semiparametric model is considered to be a useful and flexible specification for studying a general regression relationship with varying coefficients. 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.

\[ T\hat{P}_{it} = W_{it}^T\beta + \theta(V_{it})\hat{P}_{it} + u_{it} \quad (2.1.6) \]

2.2. Specification of Model 2

In order to examine our second goal, based on the data available we first model the dispersion of pollution and then we define a general production function that accounts for the transboundary spillovers of pollution.

**Transboundary pollution spillovers and productivity growth**

We use more than one ways in order to measure spillovers. One is by empirically trying to find the relationship between the two pollution measurements: ambient concentration rates and emissions. Second we model the spatial relationships between states by using weights. People usually use weights based on the geographical distance between countries (or states in our case) or by constructing weights indicating which states share a land border with each other (note that none of these assumptions are without limitations). Finally, in the environmental context, a state can affect another state due to factors like the direction of the wind, weather conditions and etc. The scientific information
concerning the atmospheric dispersion of an air pollutant takes into account all these factors and the so called “transport matrix” is used in order to transform a vector of emissions into a vector of depositions for each country or state\textsuperscript{2}. We don’t have any information on transport matrices for the U.S. states for now\textsuperscript{3}.

Transboundary pollution spillovers
In order to estimate the part of the concentration rate of pollution that is attributed to a state’s “own pollution” and the part attributed to pollution spillovers, we use the two pollution measures: ambient concentration rates and emissions. The concentration rate of pollution produced by state \textit{i} is unknown. That is, the concentration rate of pollution in the atmosphere resulting from emissions produced within state \textit{i} is not measured. What is recorded (and is the information we have in our data set) is the concentration rate, \(C_{it}\), measured in the atmosphere of state \textit{i}. \(C_{it}\) can possibly include pollution spillovers from other states. In other words total concentration rate in state \textit{i} at time \(t\), \(C_{it}\), is assumed to depend on the unknown concentration rate produced by state \textit{i} at time \(t\), and on pollution coming in the state from other states minus the pollution going out of the state

\[
C_{it} = C_{it}^{own} + S_{it} - S_{jt}
\]

where \(S_{it}=\Sigma_{i\neq j}w_{ij}C_{jt}\) is the sum of the weighted pollution coming in state \textit{i} and \(S_{jt}=\Sigma_{i\neq j}w_{ij}C_{it}\) is the sum of the weighed pollution going out from state \textit{i} (the weight \(w_{ij}\) is zero). In order to measure the unknown concentration rate produced by state \textit{i} we use the state’s own stock of emissions per square km as a proxy (we believe that the stock of emissions per square km is a better proxy than current emissions per square km). We use the sum of the weighed concentration rate of states other than state \textit{i} as a proxy for pollution “spillins”\textsuperscript{4}.

\textsuperscript{2} In 1995, the estimated transboundary flow of SO2 from the USA to Canada was between 3.5 – 4.2 millions of tons per year (Meteorological Service of Canada, http://www.ec.gc.ca/acidrain/acidrainfact.html).

\textsuperscript{3} The analysis with weights is only preliminary and as such is omitted from the present draft.

\textsuperscript{4} For now we account only for pollution received by a state and not for pollution going out of a state.
Putting it all together, concentration rates are assumed to be an unknown function of the stock of emissions per square km, $P_{it}$ and the spillover pollution, $S_{it}$ i.e. $\mu(P_{it})$ and $\omega(S_{it})$. The following equation is estimated using nonparametric marginal integration methods.

$$ C_{it} = \alpha + \mu(P_{it}) + \omega(S_{it}) + \nu_{it} \quad (2.2.1) $$

where $E(\nu_{it}/P_{it}, S_{it})=0$, $\alpha$ is an unknown parameter, $\mu(.)$ and $\omega(.)$ are unknown univariate functions that satisfy the identifiably condition that $E(\mu(P_{it}))=0$ and $E(\omega(S_{it}))=0$. The additive components $\mu(.)$ and $\omega(.)$ in equation (2.2.1) can be consistently estimated at the same rate as a fully non-parametric regression with only one regressor (Stone (1985,1986)). In some sense the additive regression model provides a way of tackling the problem of the “curse of dimensionality”; one of the most important weaknesses of non-parametric estimation methods. Linton and Nielsen (1995), Fan, Hardle and Mammen (1998) and Fan and Li (2003) use marginal integration in order to estimate the components of the additive regression model.

The estimated functions of $\mu(.)$ and $\omega(.)$ are then used in the production function (defined below) and represent a state’s “own pollution” and “pollution received” respectively.

**TFP model and pollution spillovers**

To examine the second goal of this paper we define a general production function that accounts for the transboundary spillovers of pollution

$$ Y_t = F(X_t, f(P_{it}), g(S_{it}), t) \quad (2.2.2) $$

where $f(.)$ and $g(.)$ are the estimated functions of $\mu(.)$ and $\omega(.)$ respectively from the estimation of equation (2.2.1).

To determine the effect of “own pollution” as well as the effect of “pollution originating from other states” in the production process we follow again the approach based on
Mamuneas, Savvides and Stengos (2006). Total differentiation of (2.2.2) with respect to time and division by Y yields:

$$\dot{Y} = \dot{A} + \varepsilon_k \dot{K} + \varepsilon_L \dot{L} + \varepsilon_f \dot{f}(P_{it}) + \varepsilon_g \dot{g}(S_{it})$$  \hspace{1cm} (2.2.3)

where (·) denotes a growth rate, $\dot{A} = (\partial F/\partial t)/Y$ is the exogenous rate of technological change and $\varepsilon_i = (\partial \ln F)/(\partial \ln Q_i)$, ($Q_i=K,L,P$) denotes output elasticity. Subtracting from both sides of equation (2.2.3) the contribution of traditional inputs to the output growth we get

$$\dot{Y} - \varepsilon_k \dot{K} + \varepsilon_L \dot{L} = \dot{A} + \varepsilon_f \dot{f}(P_{it}) + \varepsilon_g \dot{g}(S_{it})$$  \hspace{1cm} (2.2.4)

As before, the left hand side of equation (2.2.4) 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 (2.2.4). 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:

$$TFP_{it} = \dot{Y}_{it} - w_{L_{it}} \dot{L}_{it} - w_{K_{it}} \dot{K}_{it}$$  \hspace{1cm} (2.2.5)

where $w_{Q_{it}} = 0.5(s_{Q_{it}} + s_{Q_{it-1}})$, ($Q_i=K,L$) are the weighted average income shares of labor and physical capital and $Q_u = \ln Q_u - \ln Q_{u-1}$, ($Q=Q,Y,L,K$). Same as in model 1, 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 (2.2.4). The unobserved contribution of “own pollution” and “pollution received” to output growth is assumed to be an unknown function of both $P_u$ and $S_u$. That is $\theta_i(.)\hat{f}$ and $\theta_i(.)\hat{g}$. 

Hence, putting all together, equation (2.2.4) can be written as:

\[ T\hat{F}P_{it} = \hat{A}_{it} + \theta_1(.) \hat{f}(P_{it}) + \theta_2(.) \hat{g}(S_{it}) + u_{it} \]  

(2.2.6)

Again, as before, \( \hat{A}_{it} \) can be considered as a function of state and year specific dummy variables. This together with the assumption that the unknown functions \( \theta_1(.) \) and \( \theta_2(.) \) depend on the level of “own pollution” and “pollution received” define the equation of interest as:

\[ T\hat{F}P_{it} = a_0 + \sum_{i=1}^{N-1} a_i D_i + \sum_{t=1}^{T-1} a_t D_t + \theta_1(f(P_{it}), g(S_{it})) \hat{f}(P_{it}) + \theta_2(f(P_{it}), g(S_{it})) \hat{g}(S_{it}) + u_{it} \]

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

\[ T\hat{F}P_{it} = W_{it}^T \beta + \theta_1(V_{it}) \hat{f}(P_{it}) + \theta_2(V_{it}) \hat{g}(S_{it}) + u_{it} \]  

(2.2.7)

For proper estimation we assume that \( E(u_{it} | W_{it}^T, V_{it}, \hat{f}(P_{it}), \hat{g}(S_{it})) = 0 \).

The model of equation (2.2.7) is estimated using a smooth varying coefficient semiparametric estimator.

In summary, the implications to be tested using models 1 and 2 are:

- Estimation of the effect of pollution on TFP growth using the framework in model 1. Pollution spillovers are not taken into account and pollution we use is measured in both emissions and concentration rate terms.

- Estimation of the effect of “own pollution” and “pollution received” on TFP growth using the framework in model 2. This model takes into account transboundary pollution spillovers.
3. Data
The data is a panel data set with information on the 48 U.S. states for the years 1977-2002. To construct the Total Factor Productivity (TFP) index for each U.S. state we use data on output, labor and capital stock by state in the private non-farm sector. All variables are in millions of 2000 U.S. $. Output, Y is defined as the GDP in constant prices (2000), Labor, L is defined as the total man-hours (total number of workers times hours worked). Capital stock, K by state is not available so we construct it. We use the perpetual inventory method to do so. For this purpose we construct gross investment in constant prices by state as well as the depreciation rate by state. We use two pollution measures for two pollutants: emissions (thousand tons) and concentration rates (parts per million-ppm) of SO2 and NOx. Further details about sources and construction of variables are given in the appendix.

Concentration rates vs. Emissions-Discussion
Before analyzing the results we provide a brief discussion and some more information regarding the pollution data. Ambient concentration rates are recorded in various stations across counties within a state. That is, they are air quality measurements. Emissions on the other hand are not measured but calculated based on estimations of the tons of fuel consumed and they are derived at the plant or county level and aggregated to the state level. The difference between the emissions produced by a state and the ambient concentration rate in a state can be used as a proxy for possible pollution spillovers between the U.S. states. But it should be noted that emissions cannot be directly translated into concentration rates because part of the air emissions is removed from the atmosphere (assimilative capacity of nature) or chemically transformed.

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5 In most of the literature people use the state capital constructed by Munnel (1990): These data are for the time period 1970-1986, so this restricts the period of any sample that uses this capital stock. Munnell apportions the BEA total for agriculture, manufacturing, and nonagriculture-nonmanufacturing using gross book value data from the economic censuses that occur every five years (1972, 1977, 1982, and 1987). Also Garofalo and Yamarik (2002) constructed capital by state for the years 1947-2001.
According to EPA changes in concentration rates do not always follow the changes in emissions. EPA identifies some main reasons for this. Firstly, the location of the monitors matter. If the monitors are located in urban areas then they will capture mainly urban emissions (from mobile sources) and not stationary sources (e.g. power plants) that are mainly located in rural areas. Secondly, chemical reactions in the atmosphere occur during the time that the pollutants travel from the source to the monitoring station. Thirdly, meteorological conditions affect the formation and the accumulation of the pollutants in the ambient air (wind can transfer pollutants miles away from its source-transboundary pollution). We can also add another reason; even though emissions are falling they can still be above the assimilative capacity of nature (probably due to the stock of emissions accumulated) thus increasing the concentration rate of the pollutant in the atmosphere.

Because of the way these two data sets (concentration and emission data) are recorded they inherit measurement problems (see Lieb, C.M., 2003):

- Concentration rates vary widely over time and space. So these data are noisy and suffers from comparability problems over time
- Site selection bias: monitoring stations are often located at sites where pollution is considered to be an actual or potential problem (Grossman, 1995). This results in overestimating concentration rates (Borghesi, 1999)
- Monitoring stations are set probably when pollution is high and rising. That is, again the concentration rates can be overestimated.

But the data are improving over time (see Brock and Taylor (2005)).

The two measures of pollution, due to the way they are measured, differ in the way they are related to local economic activity. Concentration rates measure the local impact in the environment but their relationship with local economic activity is not as clear due to the problem of transboundary pollution spillovers (the problem is worse when the pollutant is

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long-lived and transboundary). On the other hand emissions are directly related to local economic activity but do not account for the location of the impact of these emissions. If the aim is to examine the relationship between pollution and local economic activity, then it seems that using the measure of emissions is more appropriate (Ansuategi, 2003).

We follow Ansuategi (2003), Kalaitzidakis, Mamuneas and Stengos (2008), and use emission density (tons per square kilometer) as an indicator of environmental degradation. We then use two variants of emission density measure: current emission density and the stock of accumulated emission density. The latter is used to account for the fact that part of a pollutant is removed once released in the atmosphere due to both human activities as well as natural processes-assimilative capacity of nature.

To summarize, the concentration rate measure is not the best indicator in capturing the relationship between environmental damage and local economic activity due to possible “spillins” from and “spillouts” to other states but it measures the local impact in the environment. In this sense this measure captures the immediate impact of pollution on human health and in the environment in general. If one does not care from where pollution came from or where pollution went to, then concentration rates simply measure the local effect on the environment. On the other hand by using the emission density measure we capture the effect of local economic activity but we ignore the location that the locally produced emissions are accumulated.

Since concentration rates and emissions capture different aspects of pollution we decided to estimate the relationship of pollution and state TFP growth using both measures. In turn, we estimate the relationship between emissions and concentration rates in order to measure “own pollution” and “pollution received”.

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7 There are of course other factors like chemical transformation and etc. mentioned above.
8 Following scientific evidence for other pollutants (e.g. CO2) we assume that the rate deterioration of the emissions stock is 0.3 for NOx and 0.4 for SO2. We also used other rates in the estimations and it seems that when these rates are between 0.2-0.6 the results do not change significantly.
Descriptive statistics
In figure 1 we graph emissions and concentration rates of SO2 and NOx for the period 1977-2002. In figures 2 and 3 we graph emissions per unit of output quantity and concentration rates per unit of output quantity for the period 1977-2002. Following Brock and Taylor (2005) we normalize our measures to 100 in 1977 for comparison convenience.

According to figure 1 emissions of NOx during this period fell on average by 17% and emissions of SO2 by 50%. The concentration rate of SO2 fell by approximately 50% and the concentration rate of NOx by approximately 10%. According to figures 2 and 3 emissions per unit of output fell by approximately 80% for both SO2 and NOx. The concentration rate of SO2 per unit of output fell by approximately 80% whereas the concentration rate of NOx per unit of output fell by approximately 50%. Output quantity was also normalized to 100 in 1977 and as the graph shows that it was more than doubled (124%).

According to EPA’s findings, for the period 1970-2002 (period of active regulation by EPA) NOx emissions dropped by 17% in 2002 compared with 1970 and SO2 emissions dropped by 52% for the same period-very close to our calculations for the period 1977-2002. Also, nationally, average SO2 ambient concentrations have been cut by

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9 It should be noted that the concentration rate of NOx had a lot of missing values and as such the results concerning the concentration rate of NOx should be read with caution.
approximately 54 percent (there is no information for NOx concentration rates, only for NO2). For the same period, U.S. GDP rose by 164%\(^\text{10}\).

4. Empirical analysis and findings

In this section we present the results for models 1 and 2. We estimate the relationship between pollution and TFP growth using a parametric framework as well as nonparametric techniques that allow for a flexible functional form. As far as the nonparametric model, we are interested in the unknown function(s) \( \theta(.) \) that measure(s) the elasticity of pollution for each state and each period. The results presented here are based on standard local kernel estimation using the standard Gaussian density as the kernel and applying cross-validation to obtain the smoothing parameter.

Results of Model 1

We obtain estimates of \( \theta(.) \), the output elasticity of pollution along with estimates of the coefficients in the linear part of the model. The estimates are for the three different measures of pollution we use; concentration rates, emissions per square kilometre and stock of emissions per square kilometer. The figures with the results of model 1 are presented bellow. To conserve space the table with the point estimates of the output elasticity of pollution is given in the appendix.

Concentration rates

Semiparametric PLR model

For SO2, for most of the states in the sample, the average effect of pollution on TFP growth is negative. This is also the case for NOx but the results should be viewed with caution because of missing values. As argued above, the relationship between concentration rates and local economic activity is unclear but what is clear is that concentration rates measure the local impact on the environment. Keeping this in mind,

\(^{10}\) The difference between our figures and that of EPA’s is that we use state level measures to calculate the national average. Also some states are excluded from our calculations. EPA is using national figures to begin with. The numbers here are from the EPA’s: Latest Findings on National Air Quality, 2002 Status and Trends, \url{http://www.epa.gov/air/airtrends/aqtrnd02/2002_airtrends_final.pdf}.
the results indicate that the negative externality effect of pollution (effect on the environment) dominates the productivity effect.

Figures 4 and 5 plot pointwise estimates of the output elasticity of concentration rates, $\theta(.)$, on the vertical axis and the concentration rate level on the horizontal axis.

From the figures 4 and 5, it seems that the effect of SO2 on TFP growth is negative and constant up to a certain level of pollution and then at higher levels of pollution it seems to become positive and accelerate. For NOx, at low levels of pollution the effect on TFP growth is positive but as the level of pollution increases the effect on TFP growth becomes negative. In addition it seems that this effect is nonlinear (mainly for NOx and not for SO2). The negative effect increases, reaches a maximum point (in terms of the negative elasticities), and then the effect reverses again; at the higher levels of pollution the effect on growth becomes positive again. Before proceeding in explaining these findings it should be noted that low levels of pollution correspond to the last years of our sample whereas high levels of pollution correspond to the early years of our data. These findings are consistent with the timing of the introduction of stricter environmental regulations in the context of the EPA’s Clear Air Act. So it seems that environmental regulations, set in order to reduce the high levels of pollution, have induced technological change (new pollution abatement technologies, changes in production processes etc) which increases productivity and growth.
In table 1 of the appendix we have calculated the average output elasticity of pollution by state. The results for concentration rates are presented in the first two columns of the table. According to the results, for most of the states in the sample the average elasticity of pollution is negative. The average output elasticity of pollution for all states in the sample is -0.0003 for SO2 and -0.0009 for NOx.

**Parametric results-state fixed effects for concentration rate**
According to the parametric results, the coefficients of both SO2 and NOx are positive indicating a positive effect on TFP growth but they are statistically insignificant. Moreover a look at the interaction terms between pollution (pollution, pollution squared, pollution cubed and pollution in the 4th power) and pollution growth indicates that the relationship of SO2 with TFP growth is linear. NOx on the other hand seems to nonlinearly affect TFP growth. These results are given in table 2 of the appendix.

**Current emissions and stock of Emissions per square km**

**Semiparametric PLR model**
Here we use two measures of emissions; current emissions per square kilometer and stock of emissions per square kilometer. For both measures and for both SO2 and NOx the average effect on TFP growth is positive for almost all levels of pollution. These results indicate that the productivity effect dominates the externality effect of pollution (effect on the environment). This is in line with the arguments regarding the direct relationship between emissions and local economic activity.

The positive effect on TFP growth is higher at higher levels of emissions (early years in the sample. This is an indication that, as in the case of concentration rates above, the increasing positive effect on TFP growth is probably due to the technological advance induced in the effort of pollution reduction. Figures 6-9 plot pointwise estimates of the output elasticity of emissions, \( \theta(.) \), on the vertical axis and the emissions level on the horizontal axis. Figures 6 and 7 plot the output elasticity of current emissions per square kilometer.
kilometer whereas figures 8 and 9 plot the output elasticity of the stock of emissions per square kilometer.

By looking at the figures for NOx we observe that the effect of emissions (both current and stock of emissions) on growth increases with the level of emissions. Moreover it seems that this effect is almost linear. For SO2 the estimates present a different picture. The effect of emissions on TFP growth is positive but nonlinear. These results concerning the relationship between TFP growth and emissions are supported also from the parametric estimations discussed below. In the case of SO2 current emissions, at first the elasticity of SO2 emissions increases with the level of emissions, reaches a maximum point, reduces slightly and finally increases again. In the case of emission stock, at first the elasticity of SO2 emission stock increases with the level of emissions, reaches a
maximum point and then reduces. That is at highest levels of emission stock the positive output elasticity of pollution is falling. It seems that at these levels of SO2 emission stock, the negative externality effect dominates the productivity effect. The results indicate that the empirical relationship between emissions and TFP growth is also in line with the arguments in favour of the scenario of “technological advance” discussed in Brock and Taylor (2005). According to this scenario technological progress in the production and pollution abatement techniques (technique effect-cleaner production techniques) can result in increased productivity and growth (see Grossman and Krueger (1993), Copeland and Taylor (1994, 2004), Brock and Taylor (2005)).

The famous so called "Porter hypothesis" also supports the technological advance scenario. The "Porter hypothesis" states that "properly designed environmental standards can trigger innovation that may partially or more than fully offset the costs of complying with them". That is, the net cost of compliance can fall with stringent regulations and may even turn into a net benefit. He calls these offsets "innovation offsets" (Porter (1991) and Porter and van der Linde (1995)).

In table 1 of the appendix we have also calculate the average output elasticity of emissions by state. The results for current emissions and stock of emissions per square kilometer are presented in the last four columns of the table. According to the results the average elasticity of current emissions per square kilometer for all states in the sample is 0.0039 for SO2 and 0.0068 for NOx. The states that have the highest positive NOx elasticities are Maryland, Massachusetts and Delaware whereas the states with the highest positive SO2 elasticities are West Virginia, Ohio and Delaware. The average elasticity of the stock of emissions per square kilometer for all states in the sample is 0.0084 for SO2 and 0.0418 for NOx. The states that have the highest positive NOx elasticities are Maryland, Delaware and New Jersey whereas the states with the highest positive SO2 elasticities are Indiana, West Virginia and Delaware.
Parametric results-state fixed effects for current emissions and stock of emissions per square km
In table 2 of the appendix we report the parametric estimation results of the model. According to the results, the coefficients of both SO2 and NOx are positive indicating a positive effect on TFP growth but only for current NOx per square km is the coefficient statistically significant. A look at the interaction terms between pollution (pollution, pollution squared, pollution cubed and pollution in the 4th power) and pollution growth indicates that the relationship of SO2 with TFP growth is nonlinear. This holds for both current and stock of emissions. NOx on the other hand seems to linearly affect TFP growth.

Overall, for all pollution measures (concentration rates, current emissions and stock of emissions per square kilometre) we note that by ignoring interstate pollution spillovers, when we only use concentration rates as our measure of pollution, the effect on TFP growth is negative. On the other hand when we use emission density the effect on TFP growth is positive. This implies that in the first case the negative externality effect of pollution dominates the productivity effect whereas in the latter case the opposite is true. These results and accounting for the different nature of these two measurements led us to verify the need of explicitly accounting for the effect of a state’s “own pollution” that is the pollution produced locally and stayed within a state’s boundary and the “pollution received” from other states. That is the pollution produced outside a state’s border but transported inside the state’s area (and therefore was included in the measurements of the state’s ambient concentration rates).

Results of Model 2
In this section we estimate the effect of pollution on TFP growth by also including transboundary pollution spillovers in the analysis.

In the model presented here we attempt to find the empirical relationship between ambient concentration rates and emissions. Using marginal integration we estimate the part of concentration rates that is attributed to a state’s “own pollution” and to a state’s
“received pollution”. We use the stock of emissions per square km as the variable entering in the function that represents “own pollution” and the sum of concentration rates of all states but the state in question as the variable entering in the function that represents “received pollution”. Then we use the estimated functions of “own pollution” and “pollution received” as variables entering the production function in order to estimate their effect on TFP growth. We obtain estimates of $\theta_1(.)$ and $\theta_2(.)$, the output elasticity of “own pollution” and “pollution received” respectively along with estimates of the coefficients in the linear part of the model. We only present results for SO2 due to data availability.

**Semiparametric PLR model**

According to the results, the average effect for all states of SO2 “own pollution” on TFP growth is positive whereas the effect of “pollution received” is, as expected, negative$^{11}$. The pollution that a state receives from other states is a negative externality and as such it has a negative effect on the “receiver’s” state growth. On the other hand as far as the “own pollution” is concerned there are two offsetting effects, the productivity effect and negative externality effect; it seems that the productivity effect dominates the negative externality effect.

Figure 10 plots the output elasticity of “own pollution”, $\theta_1(.)$, on the vertical axis the and the estimated “own pollution” on the horizontal axis. Figure 11 plots the output elasticity of “pollution received”, $\theta_2(.)$, on the vertical axis the and the estimated “pollution received” on the horizontal axis.

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$^{11}$ The direction of the relationship between growth and pollution is not clear. In order to avoid possible endogeneity problems we use lagged values for the estimated own and pollution received in the production function.
According to figure 10, the effect of “own pollution” on growth is positive and increases with the level of “own pollution”, whereas according to figure 11 the output elasticities of “pollution received” are negative for most of the values of “pollution received”. In addition, especially in the case of “pollution received” it seems that the effect on growth is nonlinear. The parametric estimations (discussed below) also indicate that the relationship between TFP growth and “pollution received” is nonlinear.

In table 3 of the appendix we report the average output elasticity of pollution per state. The average elasticity (for all states) of SO2 pollution received is -0.05. That is, 1% increase of the “pollution received” decreases on average output by 0.05%. The average elasticity of “own pollution” is 0.025. The states that have the highest negative effect on TFP growth, from the SO2 pollution they receive, are the states of Ohio, Indiana, Delaware and West Virginia (on average the elasticity is -0.067 for these states). These states are in the east United States and as such they are considered to be “downwind states”. According to the U.S. EPA, the “downwind states” receive pollution from the “upwind states” (west U.S. states). Our results verify that the “big losers”, as far as the negative effect of pollution spillovers on productivity growth is concerned, are among the states classified as “downwind states” by the EPA.
**Parametric results-state fixed effects**

The effect of “pollution received” on TFP growth is negative and statistically significant. The interaction terms between “pollution received” (pollution, pollution squared, pollution cubed) and “receivable pollution” growth indicates that the relationship between “pollution received” and TFP growth is nonlinear (these terms are also statistically significant). As far the “own pollution”, the effect on growth is positive but statistically insignificant. The same is true for almost (except for the first order interaction term) all the interaction terms between “own pollution” and the “own pollution” growth. These results are given in table 4 of the appendix.

In summary the results from the estimation of model 2 indicate that by accounting for interstate spillovers in the analysis there is a positive relationship between “own pollution” and TFP growth whereas the relationship between “pollution received” and TFP growth is negative.

**5. Conclusion**

This paper measures the effect of pollution and pollution spillovers on the Total Factor Productivity growth among the U.S. states. As a measure of pollution we use two air pollutants, NOx and SO2. We use two different measures of these pollutants; ambient concentration rate and emission density. We construct a Total Factor Productivity (TFP) growth index by removing from output growth the effect of the growth of the standard inputs, capital and labor. We then examine the relationship between TFP growth and pollution using a semiparametric smooth coefficient model that allows us to directly estimate the elasticity of pollution without imposing any restriction on the functional form of the production function. Finally, following the same methodology, we try to account for the effect of interstate pollution spillovers on state level productivity growth.

Our results indicate that when we do not account for transboundary pollution spillovers and just use the two different measures of pollution, concentration rates and emissions density then their effect on TFP growth differs substantially. That is the effect of current emission density and the stock of accumulated emission density on TFP growth is
positive whereas the effect of concentration rates is negative. This implies that in the first case the productivity effect of pollution dominates the negative externality effect whereas in the latter case the opposite is true. These results and accounting for the different nature of these two measurements led us to verify the need of explicitly accounting for the effect of a state’s “own pollution” and the “pollution received” from other states. By accounting for interstate spillovers in the analysis the results indicate that there is a positive relationship between “own pollution” and TFP growth whereas in the case of the “pollution received” the relationship with TFP growth is negative. The pollution that a state receives from other states is a negative externality and as such it has a negative effect on the “receiver’s” state growth. On the other hand the relationship between “own pollution” and growth depends on two offsetting effects, the productivity effect and the negative externality effect; our results indicate that the productivity effect dominates the negative externality effect.

As already mentioned, we are in the process of investigating other specifications in order to verify the robustness of the spillover pollution analysis. We are looking at various weighting schemes that rely on the spatial information in order to assess neighborhood effects. We are also in the process of constructing weights that are based on the size of the state as well as on weather patterns.
References


Stern D., 2000. Applying recent developments in time series econometrics to the spatial domain, Prof. Geogr. 52, 37–49.


### Appendix

## Results

### Model 1

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<td>0.0019</td>
<td>0.0064</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Mean values for all states

-0.0009 -0.0003 0.0068 0.0039 0.0418 0.0084

Because of missing values only 46 out of the 48 contiguous states are included.

Table 2: Parametric results - Fixed effects model
Depended variable: TFP growth

<table>
<thead>
<tr>
<th>variables</th>
<th>Fixed effects</th>
<th>NOx</th>
<th>SO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration rates</td>
<td>P</td>
<td>.0800613</td>
<td>.0593799</td>
</tr>
<tr>
<td></td>
<td>P*growthP</td>
<td>(1.53)</td>
<td>(0.19)</td>
</tr>
<tr>
<td></td>
<td>P^2*growthP</td>
<td>-12.76636</td>
<td>6765776</td>
</tr>
<tr>
<td></td>
<td>P^3*growthP</td>
<td>252.8883</td>
<td>968.3639</td>
</tr>
<tr>
<td></td>
<td>P^4*growthP</td>
<td>-1193.054</td>
<td>-16930.58</td>
</tr>
<tr>
<td>Current Emissions, per square km</td>
<td>P</td>
<td>0.0024227</td>
<td>0.005161</td>
</tr>
<tr>
<td></td>
<td>P*growthP</td>
<td>(2.79)</td>
<td>(1.06)</td>
</tr>
<tr>
<td></td>
<td>P^2*growthP</td>
<td>-0.0008883</td>
<td>.0013705</td>
</tr>
<tr>
<td></td>
<td>P^3*growthP</td>
<td>0.0000942</td>
<td>5.24e-06</td>
</tr>
<tr>
<td></td>
<td>P^4*growthP</td>
<td>-2.65E-07</td>
<td>(-1.58)</td>
</tr>
<tr>
<td>Stock of Emissions, per square km</td>
<td>P</td>
<td>.0004118</td>
<td>.0000426</td>
</tr>
<tr>
<td></td>
<td>P*growthP</td>
<td>(1.13)</td>
<td>(0.19)</td>
</tr>
<tr>
<td></td>
<td>P^2*growthP</td>
<td>-0.001037</td>
<td>.0001839</td>
</tr>
<tr>
<td></td>
<td>P^3*growthP</td>
<td>3.14E-05</td>
<td>-3.57e-06</td>
</tr>
<tr>
<td></td>
<td>P^4*growthP</td>
<td>-2.65E-07</td>
<td>(-1.92)</td>
</tr>
</tbody>
</table>

Because of missing values only 46 out of the 48 contiguous states are included.

Note: t-statistics in parenthesis
### Model 2

**Table 3: Elasticities of estimated own and received pollution for SO2.**

Mean values by state 1978-2002

<table>
<thead>
<tr>
<th>State</th>
<th>“Estimated Own Pollution” Elasticity</th>
<th>“Estimated Received Pollution” Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>0.036</td>
<td>-0.049</td>
</tr>
<tr>
<td>Arizona</td>
<td>0.018</td>
<td>-0.048</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.023</td>
<td>-0.044</td>
</tr>
<tr>
<td>California</td>
<td>0.019</td>
<td>-0.045</td>
</tr>
<tr>
<td>Colorado</td>
<td>0.019</td>
<td>-0.046</td>
</tr>
<tr>
<td>Connecticut</td>
<td>0.035</td>
<td>-0.050</td>
</tr>
<tr>
<td>Delaware</td>
<td>0.038</td>
<td>-0.066</td>
</tr>
<tr>
<td>Florida</td>
<td>0.036</td>
<td>-0.045</td>
</tr>
<tr>
<td>Georgia</td>
<td>0.032</td>
<td>-0.052</td>
</tr>
<tr>
<td>Idaho</td>
<td>0.019</td>
<td>-0.049</td>
</tr>
<tr>
<td>Illinois</td>
<td>0.029</td>
<td>-0.057</td>
</tr>
<tr>
<td>Indiana</td>
<td>0.026</td>
<td>-0.068</td>
</tr>
<tr>
<td>Iowa</td>
<td>0.024</td>
<td>-0.046</td>
</tr>
<tr>
<td>Kansas</td>
<td>0.020</td>
<td>-0.046</td>
</tr>
<tr>
<td>Kentucky</td>
<td>0.033</td>
<td>-0.056</td>
</tr>
<tr>
<td>Louisiana</td>
<td>0.029</td>
<td>-0.046</td>
</tr>
<tr>
<td>Maine</td>
<td>0.020</td>
<td>-0.047</td>
</tr>
<tr>
<td>Maryland</td>
<td>0.028</td>
<td>-0.053</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>0.014</td>
<td>-0.064</td>
</tr>
<tr>
<td>Michigan</td>
<td>0.027</td>
<td>-0.044</td>
</tr>
<tr>
<td>Minnesota</td>
<td>0.020</td>
<td>-0.045</td>
</tr>
<tr>
<td>Mississippi</td>
<td>0.025</td>
<td>-0.045</td>
</tr>
<tr>
<td>Missouri</td>
<td>0.025</td>
<td>-0.058</td>
</tr>
<tr>
<td>Montana</td>
<td>0.020</td>
<td>-0.048</td>
</tr>
<tr>
<td>Nebraska</td>
<td>0.020</td>
<td>-0.044</td>
</tr>
<tr>
<td>Nevada</td>
<td>0.021</td>
<td>-0.044</td>
</tr>
<tr>
<td>New Hampshire</td>
<td>0.035</td>
<td>-0.048</td>
</tr>
<tr>
<td>New Jersey</td>
<td>0.033</td>
<td>-0.055</td>
</tr>
<tr>
<td>New Mexico</td>
<td>0.020</td>
<td>-0.046</td>
</tr>
<tr>
<td>New York</td>
<td>0.031</td>
<td>-0.054</td>
</tr>
<tr>
<td>North Carolina</td>
<td>0.032</td>
<td>-0.045</td>
</tr>
<tr>
<td>Ohio</td>
<td>0.038</td>
<td>-0.069</td>
</tr>
<tr>
<td>Oklahoma</td>
<td>0.020</td>
<td>-0.047</td>
</tr>
<tr>
<td>Oregon</td>
<td>0.020</td>
<td>-0.046</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>0.015</td>
<td>-0.059</td>
</tr>
<tr>
<td>Rhode Island</td>
<td>0.026</td>
<td>-0.047</td>
</tr>
<tr>
<td>South Carolina</td>
<td>0.029</td>
<td>-0.044</td>
</tr>
<tr>
<td>Tennessee</td>
<td>0.026</td>
<td>-0.058</td>
</tr>
<tr>
<td>Texas</td>
<td>0.023</td>
<td>-0.046</td>
</tr>
<tr>
<td>Utah</td>
<td>0.018</td>
<td>-0.048</td>
</tr>
<tr>
<td>Vermont</td>
<td>0.019</td>
<td>-0.047</td>
</tr>
<tr>
<td>Virginia</td>
<td>0.031</td>
<td>-0.046</td>
</tr>
<tr>
<td>Washington</td>
<td>0.020</td>
<td>-0.047</td>
</tr>
<tr>
<td>State</td>
<td>SO2</td>
<td></td>
</tr>
<tr>
<td>---------------</td>
<td>------------</td>
<td></td>
</tr>
<tr>
<td>West Virginia</td>
<td>0.029</td>
<td>-0.066</td>
</tr>
<tr>
<td>Wisconsin</td>
<td>0.020</td>
<td>-0.051</td>
</tr>
<tr>
<td>Wyoming</td>
<td>0.023</td>
<td>-0.044</td>
</tr>
<tr>
<td>Mean values for all states</td>
<td><strong>0.025</strong></td>
<td><strong>-0.050</strong></td>
</tr>
</tbody>
</table>

Because of missing values only 46 out of the 48 contiguous states are included.

### Table 4: Parametric results for SO2 - fixed effects model, Depended variable: TFP growth

<table>
<thead>
<tr>
<th>Variable (P)</th>
<th>Using lagged estimated own and lagged estimated received Pollution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Estimated &quot;Own Pollution&quot;=P1 [f(E_{it})<em>{hat}]</em>{i,t-1}</td>
<td>1.564887</td>
</tr>
<tr>
<td>Estimated &quot;Received Pollution&quot;=P2 [(g(ΣC_{jt}))<em>{hat}]</em>{i,t-1}</td>
<td>-20.73682</td>
</tr>
<tr>
<td>P1*growthP1</td>
<td>187.548</td>
</tr>
<tr>
<td>P2*growthP2</td>
<td>-61962.54</td>
</tr>
<tr>
<td>P1^2*growthP1</td>
<td>5014240</td>
</tr>
<tr>
<td>P2^2*growthP2</td>
<td>5014240</td>
</tr>
</tbody>
</table>

Because of missing values only 46 out of the 48 contiguous states are included. Note: t-statistics in parenthesis.
Data construction and sources

The sample consists of 48 states for the period 1977-2002 or a total of 1200 observations.

Output
Output by state is the GDP in constant 2000 U.S. dollars for the private non-farm sector (source: Bureau of Economic Analysis, BEA).

Labor
Labor by state in constant 2000 U.S. dollars is defined as the total man-hours in the private non-farm sector. It is the total number of workers times hours worked. Data on the total number of workers by state is from the BEA. Only industry data for the nation are available for the hours worked (source: Bureau of Labor Statistic, BLS). We construct yearly hours worked by state by summing (over the industries) the weighted hours of work for each industry in each state. The weight used is the percentage of each industry’s GDP to the sum of all industries’ GDP.

Capital
We use physical capital in constant 2000 U.S. dollars. Physical capital by state is not available so we construct it. We use the perpetual inventory method to do so. For this purpose we construct gross investment in constant prices by state as well as the depreciation rate by state. Data are obtained from the Bureau of Labor Statistics, Office of Productivity and Technology. To construct gross investment by state we summed (over sectors) the weighted gross investment for each sector in each state. The weight used is the percentage of each sector’s GDP, in each state, to the national GDP for each sector. Depreciation rate by state is the weighted sum (over sectors) of sector depreciation rate. The weight used is the percentage of each state’s gross investment by sector to the total state gross investment.
**Emissions**

The emissions data by state are measured in tons. These data are obtained from the U.S. Environmental Protection Agency (EPA) National Air Pollutant Emission Trends and National Emissions Inventory (NEI), Emissions Inventory & Analysis Group; Air Quality Assessment Division, Office of Air Quality Planning and Standards.

**Concentration rates**

Concentration rate by state is measured in parts per million by volume. These data are obtained from the U.S. Environmental Protection Agency (EPA), webpage: [http://www.epa.gov/aqspubl1/annual_summary.html](http://www.epa.gov/aqspubl1/annual_summary.html). Ambient concentrations of pollutants in outdoor air are measured at more than 4000 monitoring stations across the country. EPA collects these data and computes a yearly summary *for each monitoring station* (maximum value, average value, number of measurements, etc.). AirData has the yearly summary values only, and not the individual hourly or daily measurements. For a detailed description of the data (manuals, definitions and guides) see the EPA site: [http://www.epa.gov/ttn/airs/airsaqs/manuals/](http://www.epa.gov/ttn/airs/airsaqs/manuals/).

For each state and for each year, there is more than one value for a given pollutant, because there is more than one station in each state. So we aggregate the air quality measurements in order to have a single value *for each state and for each year*, for a given pollutant. We used the arithmetic mean of the values of a given pollutant, for each state and each year. For a detailed description of the data (manuals, definitions and guides) see the EPA site: [http://www.epa.gov/ttn/airs/airsaqs/manuals/](http://www.epa.gov/ttn/airs/airsaqs/manuals/).