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U.S. State-Level Carbon Dioxide Emissions: A Spatial-Temporal Econometric Approach of the Environmental Kuznets Curve

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Abstract

One of the major criticisms of past environmental Kuznets curve (EKC) studies is that the spatiotemporal aspects within the data have largely been ignored. By ignoring the spatial aspect of pollution emissions past estimates of the EKC implicitly assume that a region's emissions are unaffected by events in neighboring regions (i.e., assume there are no transboundary pollution emissions between neighbors). By ignoring the spatial aspects within the data several past estimates of the EKC could have generated biased or inconsistent regression results. By ignoring the temporal aspect within the data several past estimates of the EKC could have generated spurious regression results or misspecified *t* and *F* statistics. To address this potential misspecification we estimate the relationship between state-level carbon dioxide emissions and income (GDP) accounting for both the spatiotemporal components within the data. Specifically, we estimate a dynamic spatiotemporal panel model using a newly proposed robust, spatial fixed effects model. This new estimation scheme is appropriate for panels with large *N* and *T*. Consistent with the EKC hypothesis we find the inverted-U shaped relationship between CO_2 emissions and income. Further, we find adequate evidence that carbon dioxide emissions and state-level GDP are temporally and spatially dependent. These findings offer policy implications for both interstate energy trade and pollution emission regulations. These implications are particularly important for the formulation of national policies related to the 2009 Copenhagen

Treaty in which the U.S. has committed to significantly reduce greenhouse gas emissions over the next twenty years.

Introduction

The debate between economic growth versus environmental degradation is just as relevant today as it was in 1972 with the publication of the "Limits to Growth" in which the authors espoused the Malthusian view that the world's ever-dwindling resource base cannot continue to support unfettered economic expansion (Meadows et al., 1972). The relevancy of the debate can be found in the recent 2010 publication of "Eaarth: Making a Life on a Tough New Planet," in which the author formulates similar arguments to the "Limits" publication.

Economists, ecologists, private industries and government decision-makers have long been interested in the relationship between economic growth and environmental quality. These relationships are often the subject of intense public policy debates such as the recent Copenhagen Treaty signed by the current presidential administration at the 2009 U.N. Climate Change Conference. Under this treaty the administration has proposed to cut greenhouse gas emissions in the U. S. by 17% by 2020 and 42% by 2030. In the U. S. many opponents to this legislation claim that it will further slow the recessionary economy we have experienced over the past two years. Supporters, on the other hand, claim the legislation is absolutely necessary to prevent irreversible global warming caused by anthropogenic emissions of greenhouse gasses.

From an ecological or environmental perspective, the assumption is often made that economic growth is bad for the environment. But, what story does the empirical data tell us? One's intuition may lead to the belief that pollution will continue unabated as a country's economy grows through time. An examination of the empirical relationship between economic growth and emissions, however, often reveals different results as evidenced by the environmental Kuznets curve (EKC) hypothesis. The EKC hypothesis describes the time path that pollution follows through a country's economic development.

This hypothesis claims that environmental degradation follows an inverted U-shaped relationship as a country's economy develops over time. One explanation for this relationship is that pollution emissions increase as a country transitions from a largely agricultural economy to an industrial one. In the early stages of economic development people are too poor to pay for abatement and disregard the environmental consequences of economic growth. As the country's industrial base expands the pollution emissions begin to increase and start to put pressure on the environment. However, as the country's economy continues to expand its people eventually become wealthier (i.e., GDP per capita grows) and they begin to place value on environmental quality. Pollution emissions reach a peak when a country's per capita income reaches a certain threshold—i.e., when the emissions have reached a level no longer considered tolerable by its people. The people then begin to form environmental regulations often through a collective decision-making process. Thus, the EKC hypothesis implies that economic growth could actually be compatible with environmental improvement if appropriate policies are adopted.

The above EKC hypothesis seems plausible enough on the surface, but testing this hypothesis becomes increasingly more complicated when one considers the empirical or theoretical issues driving the relationship between economic growth and the environment. Since the conception of the hypothesis, researchers have examined a wide variety of pollutants seeking evidence of the EKC. Separate studies have experimented with different econometric approaches, including: different orders of polynomials, fixed and random effects, semi-parametric and non- parametric techniques, splines, and different covariates specifications (Levinson, 2008). Past studies have also examined different jurisdictions and time periods. In all there has been over 100 peer-reviewed journal articles published in the past two decades related to the EKC hypothesis (Yandle, Madhusudan, & Vijayaraghavan, 2004). Certain generalizations seem to emerge across these different approaches—i.e., it seems that pollutions levels at least approximately improve for some pollutants as income per capita grows.

Despite the rather robust literature, issues regarding the spatial and temporal dependence within the data have not been thoroughly addressed. There has been more attention as of late to the temporal dependence within the data,[1] however very little attention has been paid to spatial dependence. Similarly, incorrectly omitting spatially lagged variables may cause the parameters to be biased and inconsistent. This endogeneity could potentially exist in Stern and Common's (2001) findings in which the authors find that sulphur emissions seem to increase monotonically with per capita income for their whole sample of observed countries; however, when the authors restrict their analysis to the high-income countries they found the conventional inverted U-shaped relationship; i.e., there are spatial effects within the data.

To address this deficiency within the literature we will examine the relationship between carbon dioxide emissions and GDP in the 48 contiguous states in the US from 1963-2001. Carbon dioxide accounted for 84% of U.S. greenhouse gas emissions in 2005 and is one of the largest contributors to climate change (Brown et al., 2008). The emissions estimates are based on the combustion of fossil fuels which is one of the main sources of CO_2 emissions in the U.S. According to a U.S. Environmental Protection Agency report, fossil fuel combustion produced 94.1% of the CO_2 emitted in the U.S. in 2008 (U.S. Environmental Protection Agency, 2008). We have reason to believe that that the data are spatially dependent as emissions within a particular state are affected by the emissions from its neighboring states (i.e., transboundary pollution problems). Ramirez and Loboguerero (2002) found strong spatial dependence in income levels across 98 separate countries so we have reason to believe that GDP in one state is affected by its neighbors as well. In accounting for this potential misspecification we seek to properly specify the CO_2 pollution-income relationship across the 48 contiguous states and verify the inverted-U shaped relationship within the conventional EKC proposal.

The rest of this paper is structured as follows. In the following section we will offer a brief review of the literature. Next, we set up the spatial fixed panel data model. We then provide a description of the data used to estimate this model and present the empirical estimation procedures and results. Finally, we will discuss the empirical findings including potential policy implications and offer suggestions for further research.

[1] For example, see Stern and Common (2001), Perman and Stern (2003), and Egli (2004).

Literature Review

Rupasingha et al. (2004) were some of the first authors to offer a spatial econometric approach to the EKC hypothesis. Specifically, the authors examined the relationship between per capita income and toxic pollutants at the US county-level. With a quadratic specification the authors find the conventional inverted U-shaped relationship; however, with a cubic specification they find that toxic pollution first decreases but then increases again as income continues to grow over time (this is sometimes referred to in the literature as a N-shaped relationship). These authors' findings are interesting but the pollution-income relationship is only examined in a cross-sectional context leaving out potential dynamic effects over time.

Maddison (2006) examined the emissions of sulphur dioxide, nitrogen oxides, volatile organic compounds and carbon monoxide across 135 nations. He analyzed the conventional EKC with spatially augmented weighted values of the dependent (the pollution emissions) and independent variables (national income and other covariates) to account for potential spatial dependence within the data. The author found that national per capita emissions of sulphur dioxide and nitrogen oxides are heavily influenced by the per capita emissions of neighboring countries. Despite Maddison's (2004) contribution his analysis is limited to only two years. He took first differences of the data to control for the independent effects (fixed effects) within each country and then analyzed the data as one large cross-section. By observing only two years of data, a rich set of spatio-temporal dynamics are potentially lost which could be reconciled by offering a longitudinal or panel data approach.

Aldy (2005) offers an analysis of the EKC hypothesis applied to carbon dioxide emissions at the state-level in the US. The author used a panel data approach to estimate the pollution-income relationship between per capita CO_2 emissions and per capita income within each state. He asserted that both the CO_2 emissions and income data are non-stationary and therefore he offered a dynamic ordinary least squares (OLS) approach in addition to the conventional OLS approach (this is sometimes referred to in the literature as the least squares dummy variable model). Aldy (2005) found that the estimated inverted-U shaped relationship varied across several different specifications. The author noted that the temporal non-stationarity may yield misleading results and should therefore continue to be explored in the EKC literature. He made no mention of the potential spatial dependence within the data however.

Methodological Approach

To control for spatial dependence, temporal dependence, and state-level independent effects we propose a fixed effects estimation procedure as follows. First we specify a dynamic panel data model (i.e., include a lag term of the dependent variable) because it is a parsimonious way of accounting for persistent effects within the explanatory variables in the past. Therefore, we include a lag term of CO_2 emissions because as a stock pollutant we believe it to display some persistency along the time dimension (i.e., emissions from the previous period largely determines emissions in the current period). Specifically, the model we consider is

$$y_t = \rho y_{t-1} + X_t \beta + \mu_i + u_t, \qquad (1)$$

where y_t denotes a $N \times 1$ vector of U.S. state-level per capita carbon dioxide emissions which are stacked as successive cross-sections over time for $t = 1, \ldots, T$. ρ denotes the scalar coefficient on the time lagged value of CO_2 emissions. X_t is an $N \times K$ matrix of the explanatory variables including per capita GDP and per capita GDP squared; therefore, β is $K \times 1$ vector of coefficients on the explanatory variables. μ_i denotes the individual effect for each U.S. state. In the present analysis we treat the individual effect as fixed meaning that we assume that this variable is correlated with the explanatory variables and approximately "fixed" over time for each state within the sample. This fixed effect may be thought of as state infrastructure, political structure, topography, basic weather patterns, etc. We could estimate μ_i directly by adding a dummy variable for each cross-section and estimating the equation via ordinary least squares; this is sometimes referred to as the least squares dummy variable estimator (LSDV).[2] If we

[2] In order to conduct the LSDV estimator we must eliminate the constant term in the matrix X_t or add the constraint to μ_i such that $\sum_i \mu_i = 0$, otherwise the individual effect (dummy variable) would be indistinguishable from the intercept term.

allow for the fixed effects term to enter into the error term and we estimate (1) without controlling for it, then the estimates will result in omitted variable bias. To control for fixed effects without including a fixed effects term in (1), we could demean the data (fixed effects or within estimator) or take the first difference of the data (first-difference estimator). Econometric theory tells us that the LSDV estimator is asymptotically equivalent to the fixed effects estimator.

To complicate the model a little further, we now assume that emissions and income in one state are affected by emissions and income in other states; i.e., spatial dependence. Specifically, we assume a spatial autoregressive error process as follows where the error term u_t is defined as,

$$\begin{aligned} u_t &= \lambda W u_t + \varepsilon_t \\ E(\varepsilon_t) &= 0 \\ E(\varepsilon_t \varepsilon_t') &= \sigma_\varepsilon^2 I_N . \end{aligned} \qquad (2)$$

With (2) above we can assume that ε_{it} is a white noise process or we can make the stronger assumption that the error terms are i.i.d. for all i and t with mean zero and variance σ_ε^2. I_N is an identity matrix of size N. λ is the coefficient on the spatial autocorrelation term. W denotes an $N \times N$ non-negative spatial weight matrix consisting of zeros along the diagonal and elements w_{ij} elsewhere. w_{ij} is measure of the *a priori* strength of the interaction between location i (the row of the W matrix) and location j (the column) (Anselin, Le Gallo, and Jayet, 2008). In the simplest case the weights matrix is binary with $w_{ij} = 1$ when i and j are neighbors and $w_{ij} = 0$ otherwise.[3] In the spatial econometrics literature the weights are generally standardized such that the elements in each row sum to one (row standardization). According to Anselin et al. (2008), the specification of the spatial weights matrix is of great import in applied spatial econometrics. Initially we will assume a first-order contiguity specification (i.e., a state's emissions are affected by the emissions of states that share a common border). This assumption will be relaxed later to consider an alternative weighting specification based on the distance between state centroids. Finally, we assume the weights remain constant over time. Alternative specifications may allow the scalar parameter to vary over time or allow the weights to vary and the parameter to remain constant. Such specifications

[3] Hence the zeros along the diagonal since a state cannot be a neighbor to itself.

would only complicate the analysis, so to keep the empirical approach tractable we assume constant weights across time.

To see how the assumption of spatial autoregressive errors affects (1) we can rewrite (2) as,

$$\begin{aligned} (I_N - \lambda W)u_t &= \varepsilon_t \\ u_t &= (I_N - \lambda W)^{-1}\varepsilon_t . \end{aligned} \tag{3}$$

We can now plug (3) into (1) and rewrite some terms to derive,

$$\begin{aligned} (I_N - \lambda W)y_t &= (I_N - \lambda W)\rho y_{t-1} + (I_N - \lambda W)X_t\beta + (I_N - \lambda W)\mu_i + \varepsilon_t \\ y_t &= \rho y_{t-1} + X_t\beta + \mu_i + \lambda W(y_t - \rho y_{t-1} - X_t\beta - \mu_i) + \varepsilon_t . \end{aligned} \tag{4}$$

From an econometrics perspective the issue with estimating (1) or (4) is a problem of endogeneity. If one estimates equation (1) without taking the spatial effects into account then it is a problem of omitted variable bias (OVB) which potentially causes biasedness in parameter estimates. The problem with estimating (4) is that y_t on the RHS is jointly determined with the error term in each cross-section; i.e., there is a simultaneity problem (Anselin et al., 2008). This simultaneity can cause ordinary least squares (OLS) and least squares dummy variable (LSDV) estimators to be biased and/or inconsistent. This simultaneity can be accounted for through instrumentation (IV or GMM) or by specifying a complete distribution model (maximum likelihood). Elhorst (2005) developed a complicated unconditional maximum likelihood estimator for dynamic, spatial panel data in which he takes the first difference of the data to eliminate the fixed effects term. The problem with Elhorst's procedure is that it requires the awkward assumptions about the initial conditionals for y_0 and X_0. Bond (2002) criticizes this procedure by stating that the distributions of both y and X for t = 2, 3, …, T could depend in a "non-negligible" way on what is assumed about the initial condition (especially if T is short).

Another potential strategy for estimating (1) – (2) is to perform the conditional maximum likelihood (CML) estimation procedure. Hsaio et al. (2002) show that with dynamic panels the LSDV estimator is asymptotically equivalent as the CML estimator. Since LSDV can be biased or inconsistent in the presence of simultaneity this calls into question the appropriateness of the CML procedure. Further, Hsaio et al. (2002) show that the LSDV or CML estimators are inconsistent if T is finite and N

tends toward infinity (i.e., the incidental parameters problem).[4] Anselin et al. (2008) cast further doubt on this estimation procedure as they posit that LSDV is generally not recommended in spatial models.

A third possible estimator for (1) – (2) is the Generalized Method of Moments (GMM). Roodman (2006) though suggests only using GMM with "small *T*, large *N*" panels because the dynamic panel bias (Nickel 1981) becomes insignificant as *T* grows and he states, "a more straightforward fixed effects estimator [is appropriate]." Elhorst (2003) offers a fixed effects (FE) estimator for panel data but Anselin, et al. (2008) argue that it is biased.[5]

Given that our panel consists of $T = 39$ the asymptotics of CML estimator is questionable and following Roodman's (2006) advice the GMM may not be appropriate. Elhorst's (2005) unconditional ML estimator is attractive but too complicated, and since Elhorst's (2003) FE estimator is biased we propose the following iterative Spatial Fixed Effects (SFE) estimator which is consistent, asymptotically normal and robust to heteroskedasticity and serial correlation.[6] In principal the SFE estimator is also far simpler to compute than GMM, Elhorst's unconditional ML, and Elhorst's FE estimator. To begin we rewrite (1) and (2) by dropping the time subscript for ease of exposition (the variables are still stacked as successive cross-sections over time).

$$y = z\gamma + (I_T \otimes \mu) + u \tag{5}$$

$$u = \lambda W u + \varepsilon, \tag{6}$$

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[4] Alternatively, the LSDV and CML estimators are consistent if *T* tends toward infinity, although Hsaio et al. (2002) do not proscribe a length of *T* to maintain consistency.

[5] See the Appendix below for an explanation for why Elhorst's FE estimator is biased.

[6] For a full treatment of the SFE estimator including Monte Carlo comparisons to other estimators we refer the reader to Burnett and Bergstrom (2010).

where $z = (y_{-1} \ \ X)$, $\gamma = (\rho \ \ \beta)'$, and the weighting matrix $W = (I_T \otimes W_N)$. I_t is an identity matrix of dimensions T x T and the subscript N on W indicates that it is of dimensions N x N. Following Anselin et al. (2008) we define the "within" transformation operator as[7]

$$Q = I_{NT} - \left(\frac{\iota_T \iota_T'}{T} \otimes I_N \right),$$

where I_{NT} is an identity matrix of NT x NT and ι_T is a vector of ones of length T. We can multiply the within transformation operator through (5) and (6) to eliminate the fixed effects term, μ, as follows

$$Qy = Qz\gamma + Qu \tag{7}$$

$$Qu = \lambda WQu + Q\varepsilon . \tag{8}$$

Following Ord (1975) we can estimate γ by least squares relying upon the assumption that if T is large then the dynamic panel bias becomes insignificant. Ord (1975) states that if the spatial autocorrelation parameter (λ) is unknown, even a constrained least squares procedure produces inconsistent estimators. He defines an iterative procedure that we extend here to a panel data model:

1. Compute the GLS residuals from (7) to derive $Q\tilde{u}$ [8]
2. Estimate $\tilde{\lambda}$ from $Q\tilde{u} = \lambda WQ\tilde{u} + Q\varepsilon$ by using the Newton-Raphson Method to derive $\tilde{\lambda}$.
3. Construct new variables $\tilde{y} = (I_{NT} - \tilde{\lambda}W)Qy$ and $\tilde{z} = (I_{NT} - \tilde{\lambda}W)Qz$
4. Apply OLS for $\tilde{y}$ on $\tilde{z}$ to yield $\hat{\gamma}$.
5. Construct the new residuals $\hat{\tilde{u}} = \tilde{y} - \tilde{z}\hat{\gamma}$ and return to Step 2 to calculate $\hat{\lambda}$.
6. Construct the robust covariance for $\hat{\gamma}$ by calculating $\hat{A} = \frac{N}{N-K}(\tilde{z}'\hat{\tilde{u}}\hat{\tilde{u}}'\tilde{z})$. [9]

[7] By within transformation this means that each cross-section is demeaned "within" its own section; e.g., all the CO_2 emissions in Wisconsin will be demeaned based upon the mean of emissions from Wisconsin. The reader should note that the demeaning operator is slightly different from the operator within the traditional panel data models because the data is organized differently.

[8] Notice we use the GLS procedure because Q^{-1} does not exist since it is idempotent. Instead we use the pseudo-inverse (or Moore-Penrose Inverse) as defined in Hsiao (2003).

Conveniently this same iterated procedure can be performed with a panel first-difference (FD) estimator. We refer to this procedure as the iterated spatial first-difference (SFD) estimator. The algorithm is almost identical to the SFE procedure (for the specific algorithm please refer to the Appendix). Like the SFE, depending on certain assumptions the SFD estimator is consistent, asymptotically normal, and contains standard errors robust to heteroskedasticity and serial correlation.[10]

Data Description

CO_2 Emissions

The CO_2 emissions data were obtained from the Carbon Dioxide Information Analysis Center (CDIAC) within the U.S. Department of Energy (Blasing et al., 2004). CDIAC estimates the emissions by multiplying state-level coal, petroleum, and natural gas consumption by their respective thermal conversion factors. This gives the authors the ability to calculate the amount of heat energy derived from fuel combustion. Therefore, this dataset represents estimates of CO_2 emissions and not actual emissions, which is somewhat problematic as actual emissions data would be more desirable. The reason for using this particular dataset, however is that it offers emissions estimates dating back to the 1960, well before the establishment of the Environmental Protection Agency (EPA) and stronger enforcement of the U.S. Clean Air Act. Most CO_2 emissions data are only available after the establishment of the EPA (i.e., from the 1970s onward).[11] Therefore, we use this dataset because it offers observations before the

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[9] $\hat{A}$ is often referred to as the meat of the sandwich from the "sandwich estimator;" for further information about this procedure we refer the reader to Burnett and Bergstrom (2010). The term *(N / N – K)* is a degrees of freedom correction since $\hat{\tilde{u}}$ is biased.

[10] For more specifics with the SFD estimator we refer the reader to Burnett (2010).

[11] We believe that the establishment of the EPA coupled with stronger enforcement of the Clean Air Act could potentially bias the shape of the pollution-income relationship, especially if observed emissions are collected after the 1970's which is often the case in pollution emissions data.

establishment (or enforcement) of state and national pollution emission regulations. CO_2 emissions are offered in per capita terms by dividing total state-level emissions by the state population in a given year.

GDP

The GDP data was obtained from the Bureau of Economic Analysis (BEA) within the U.S. Department of Commerce (Bureau of Economic Analysis, 2010). The BEA offers annual state-level GDP estimates from 1963 to the near present. The estimates are based on per capita nominal GDP by state. The estimates were converted to real dollars by using the BEA's implicit price deflator for GDP. Following the traditional EKC hypothesis, GDP is expected to have an inverted U-shaped relationship with CO_2 emissions; in other words, a quadratic polynomial of GDP will be specified in which the expected sign on the GDP term is positive while the expected sign on the squared term is negative. To test this specification the polynomial can be extended to higher powers to determine if the leading term is statistically significant. For example, if a cubed GDP term is positive and statistically significant, the implication is that the pollution-income relationship is N-shaped—i.e., a relationship that is characterized by an initial increase in pollution, followed by a decrease, and then an increase once again as income continues to grow through time. We hypothesize that the quadratic relationship is the correct specification.

CDD and HDD

Cooling Degree Days (CDD) and Heating Degree Days (HDD) data were obtained from the National Climate Data Center within the National Oceanic and Atmospheric Administration (National Climate Data Center, 2010). The data are offered in a state population-weighted format consistent with the rest of the data in the study. CDD (or HDD) is a unit of measure to relate the day's temperature to the energy demand of cooling (or heating) at a residence or place of business—it is calculated by subtracting 65 degrees Fahrenheit from the day's average temperature (Swanson, 2005). Residential energy consumption has been found to be highly correlated with CDD and HDD (Diaz and Quayle, 1980). Since the CO_2 emissions are estimated from energy consumption, the CDD and HDD data as quantitative indices should capture much of the year-to-year variation in energy consumption. CDD and HDD are expected to be positively related to CO2 emissions as cooler (or hotter) days would induce households or businesses to demand higher amounts of energy for cooling (or heating) a residence or place of business.

Energy Production

The energy production data were obtained from the Energy Information Administration within the U.S. Department of Energy (Energy Information Administration, 2008). The energy production data represent state-level annual production of coal, crude oil, natural gas, and renewable energies. The data are represented in physical units: short tons, barrels, and cubic feet. The production data was converted to a population-weighted format by dividing today physical units by the state's annual population estimate. Due to data limitations, the natural gas and renewable energy production measures were dropped from the analysis. The coal and oil production measures are left in levels as several of the measures contain zeros; i.e., not all states produce coal or oil. State-level production is expected to be positively related to CO_2 emissions as an increased supply in energy may make consumption of the energy more readily available for the state. For example, if a state produces coal then it is expected that that state will keep some in reserve to use in energy production within state.

Population

Annual state population data were obtained from the U.S. Bureau of Census (Population Estimates). These population estimates represent the total number of people of all ages within a particular state.

Empirical Estimation and Results

Following the traditional EKC hypothesis with the quadratic specification, we define the spatio-temporal pollution-income relationship as

$$\begin{aligned}\ln(y_{it}) = \alpha + \rho y_{it-1} + \beta_1 \ln(GDP_{it}) + \beta_2 \ln(GDP_{it})^2 + \beta_3 \ln(CDD_{it}) \\ + \beta_4 \ln(HDD_{it}) + \beta_5 prod_{it} + \mu_i + u_{it}\end{aligned} \tag{9}$$

$i = 1,\ldots,N;\ t = 1,\ldots,T$

where y_{it} is real per capita CO_2 emissions in a U.S. state and y_{t-1} denotes its lagged value. α denotes the intercept term. GDP_{it} is real per capita state-level GDP, and GDP_{it}^2 is the square of the same term. CDD_{it} is per capita cooling degree days, whereas HDD_{it} is per capita heating degree days. $prod_{it}$ denotes per capita state-level annual production of coal and crude oil. We assume fixed state-specific effects, μ_i. The state-specific effects capture heterogeneous elements within each state that may affect CO_2 emission levels. All variables with the exception of the intercept terms and energy production are expressed in natural logarithms out of the convention that the interpretation of the parameters can be expressed as elasticities.[12] The observations in (9) are available from 1963-2001 so that $T = 39$. The observations in (9) constitute the 48 contiguous states in the U.S. excluding the District of Columbia so that $N = 48$.

For ease of exposition the variables are stacked as successive cross-sections over time for $t = 1,\dots,T$. Next we place the explanatory variables into an $N \times K$ matrix X_t and place their corresponding coefficients into a $K \times 1$ matrix β and rewrite (9) as

$$y_t = \rho y_{t-1} + X_t\beta + \mu_i + u_t. \tag{10}$$

As in (2) above we define the error term as

$$\begin{aligned} u_t &= \lambda W u_t + \varepsilon_t \\ E(\varepsilon_t) &= 0 \\ E(\varepsilon_t \varepsilon_t^{'}) &= \sigma_\varepsilon^2 I_N. \end{aligned}$$

Given the assumption of the error term in (2) we can rewrite (10) as

$$y_t = \rho y_{t-1} + X_t\beta + \mu_i + (I_N - \lambda W)^{-1}\varepsilon_t \tag{11}$$

The regression equation in (11) has a spatial autoregressive process incorporated in the error term with a spatial weight matrix specified as a normalized binary contiguity matrix (we will also consider a normalized spatial weight matrix specified as the inverse distance from the state centroids).

[12] Production is not expressed in natural logs because several states had zero values for coal or oil produced which is undefined when converted to natural logs.

For a sensitivity analysis we compare the iterated SFE and SFD estimators to the other estimation schemes discussed in the Methodological Approach; i.e., LSDV, Elhorst's FE, Elhorst's unconditional ML, and GMM. Table 1 reports the estimation results based on the complete sample of 1872 observations (or 1824 observations in terms of the SFD estimator). The second column indicates the least squares dummy variable (LSDV) estimates.[13] As we noted in the Methodological Approach section above this estimation procedure yields biased estimates because of the endogeneity issue (in this context it is from OVB). Nevertheless, the LSDV estimates are used as a baseline of comparison against the other estimation schemes. Columns three and four report the results for the spatial fixed effects estimator (Elhorst, 2003) and the fixed effects, unconditional maximum likelihood estimator (Elhorst, 2005) respectively. The fifth column represents the spatial GMM estimator (Kelejian and Prucha, 1999). The sixth and seventh columns represent the spatial fixed effects and spatial first-difference estimators outlined in this paper. Unlike the other estimation schemes the LSDV estimator does not account for spatial error autocorrelation which explains the absence of an estimate for λ (the spatial autocorrelation parameter) in its column.

The LSDV estimates imply the usual inverted-U shaped relationship of the EKC hypothesis and both indicators of income are statistically significant. The positive sign on the HDD is consistent with expectations as an average increase in HDD is expected to increase the heating of buildings which in turn requires the additional combustion of fossil fuels which in turn raises CO_2 emissions. The negative sign on oil production is not necessarily consistent with expectations as an increase in oil production within a state may be expected to elevate CO_2 emissions as the burning of that fossil fuel would be more readily available within that particular state for the production of energy. It could be however that the states that are producing higher levels of oil are exporting a significant portion of their oil to other states or abroad. As expected coal production is positive and statistically significant at the five percent level.

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[13] The LSDV estimates are equivalent to the parameter estimates from Step 1 of the iterated SFE as predicted by econometric theory.

Looking across the different estimation schemes, the estimates for the lag of CO_2 emissions are very statistically significant with the exception of the SFD estimate.[14] In the case of FE estimate we already know that it is biased and given Bond's (2002) argument about UMLE, we know that it depends in an unequivocal way on the assumptions about the initial conditions. The spatial GMM is traditionally used for cross-sectional analysis so its veracity is called into doubt here, but nevertheless a significant estimate is found. The SFE and SFD procedures find much lower estimates for the lag of CO_2 that is closer to the LSDV estimate. According to Wooldridge (2002) the choice between a standard FE and FD estimator depends on the assumptions of the idiosyncratic error term, ε. He claims that FE is more appropriate when ε_{it} are serially uncorrelated while the FD is more appropriate when ε_{it} follows a random walk. Since CO_2 is a stock pollutant we have reason to believe that ε_{it} follows a random walk; in other words, we expect a degree of persistence along the time dimension of CO_2 emissions. Therefore, the SFD may be a better estimation scheme in this case; however, Wooldridge (2002) claims that the true estimates probably lie somewhere in between the FE and FD.

In general the income and income squared terms are statistically significant across the estimates and follow the traditional inverse-U shaped relationship espoused by the EKC hypothesis (with the exception of the GMM estimator). The estimates for income and income squared with the SFD procedure are slightly lower than most of the other schemes (with the exception of the UMLE). If income is characterized by a non-stationary process (which is usually found in the literature) then first differencing

[14] If there is a high degree of persistence within CO_2 emissions (i.e., $\rho \cong 1$) then this dynamic spatial estimation scheme may inherently yield a difference stationary process for CO_2 emissions. To see this rewrite (10) as

$$\Delta y_t = (\rho - 1) y_{t-1} + X_t \beta + \mu_i + u_t ,$$

so if the true value of ρ is close to one (persistence) and the lagged emissions variables is approximately equal to zero and taking the difference yields a difference stationary process. If this is the case then SFD procedure may over-difference the CO_2 series which is biasing the estimate.

the procedure (as done with the SFD approach) may yield a difference-stationary process—in which case the SFD estimates may be more appropriate, in this instance.

Coal production was found to be statistically significant across all the estimation schemes with the exception of the UMLE procedure. All signs are positive which is consistent with expectations as we believe that an increase in coal production would increase its burning as a fossil fuel which in turn would increase CO_2 emissions. The effect is relatively small, but it is persistent across the estimators; e.g., in the case of the SFE estimate the interpretation is that a 100% increase in coal production yields a 0.1% increase in CO_2 emissions.

The spatial autocorrelation coefficient (λ) was found to be statistically significant with two of the three procedures. This significance indicates that neighboring spatial effects influence local CO_2 emissions (transboundary pollution problems). One will notice that estimates for the variance of this coefficient are absent from the SFE and SFD procedures. This unfortunately is one of the drawbacks of using these two procedures. You will recall that we used a Newton-Raphson algorithm to numerically approximate this coefficient. Since the other procedures statistically estimate this coefficient, they are able to generate its first and second moments. An approximation for the second moment of λ is currently in development. However, given that the two of three procedures find highly significant results for spatial autocorrelation, we have reason to believe the SFE and SFD procedures are appropriate.

Lastly, we follow up with Aldy's (2005) analysis where he found statistically significant results for both a quadratic and cubic specification of income. If we find statistically significant results for a cubic specification then it would imply that the pollution-income relationship is following an N-shaped path; i.e., pollution initially rises, tapers off some, and then rises again[15]. This N-shaped relationship implies that CO_2 emissions are not decreasing but increasing with income over time—this refutes the inverted U-shaped relationship. The results for the cubic specification estimates are presented in Table 2 in the Appendix. The lagged CO_2 estimate remains significant with this parametric specification;

[15] This would imply that the sign on GDP is positive, negative for GDP^2, and positive for GDP^3.

however, the income terms become insignificant for almost all of the estimation schemes. For the FE estimator only GDP is significant at a ten percent level but the other GDP terms become insignificant. With the SFD estimation scheme all the income terms are significant at a ten percent level, but the signs do not indicate an N-shaped relationship. Rather, the signs indicate that emissions initially fall then rise and then fall once again (i.e., an inverted-N relationship). Thus, there does not appear to be ample evidence to support growing CO_2 emissions over time with income which seems to offer support in favor of the traditional EKC inverted-U shaped relationship.

For sake of comparison the same estimates were produced for a different weighting matrix than the first-order contiguity matrix in Table 1. For Table 3 (located in the Appendix) we produce estimates with a weighting matrix based upon the distance from the state centroids. It is worth noting that there no real tangible differences between the two weighting mechanism; i.e., signs are similar, the same estimates are statistically significant, and R^2 values are very similar. One slight difference is that the income estimates for the SFD procedure are more significant with the distance weighting matrix. But perhaps most importantly the purported inverse-U shaped relationship still seems to hold even with a different weighting mechanism.

Table 1: Estimation Results for CO_2 Emissions—Income Relationship (Quadratic Specification)

	Model Types					
Explanatory Variables	**LSDV**	**Elhorst FE**	**Elhorst UMLE[16]**	**Spatial GMM**	**SFE**	**SFD**
$CO_{2,t-1}$	0.1003^{***} (14.8080)	0.7942^{***} (79.0542)	0.9295^{***} (124.5168)	0.6023^{***} (46.3724)	0.2190^{***} (9.3197)	0.0021 (0.6449)
GDP	8.5810^{***} (14.4590)	2.6887^{***} (6.8657)	1.3812^{**} (2.2361)	-1.5890 (-1.4829)	5.0478^{***} (5.9060)	3.8070^{**} (2.9942)
GDP^2	-0.4196^{***} (-14.318)	-0.1302^{***} (-6.8606)	-0.0652^{**} (-2.1541)	0.0716 (1.3564)	-0.2484^{***} (-5.9310)	-0.1739^{**} (-2.7698)
CDD	0.0189 (1.0665)	-0.0067 (-0.3677)	0.0108 (0.6773)	0.1070^{***} (8.5792)	0.0211 (0.7885)	0.0056 (0.7534)
HDD	0.1032^{**} (2.5290)	-0.0170 (-0.4348)	0.0469 (1.1896)	0.1431^{***} (7.7228)	0.0394 (0.8531)	0.0834^{**} (5.1630)
Coal	0.0014^{***} (9.6936)	0.0003^{***} (3.5136)	0.0002 (1.5069)	0.0013^{***} (11.3518)	0.0011^{***} (4.8842)	0.0009^{**} (2.0920)
Oil	-0.0004 (-1.5871)	0.0001 (0.7949)	0.0002 (0.9659)	0.0018^{***} (15.8662)	-0.0002 (-0.7397)	0.0005 (1.0534)
λ	N/A	0.9640^{***} (284.3158)	0.0484 (0.8870)	0.4907^{***} (11.5845)	0.2046	-0.0205
R^2	0.9288	0.3553	N/A	0.7969	0.9473	0.5684
Adjusted R^2	0.9266	N/A	N/A	0.7961	0.9471	0.5668
Robust SE	No	No	No	Yes	Yes	Yes

Notes: The numbers in the parentheses denote t-statistics. The superscripts "***", "**", "*" denote a significance level 0.01, 0.05, and 0.10 respectively. LSDV denotes the least squares dummy variable estimate.

Implications and Conclusions

Issues associated with temporal and spatial dependence have largely been ignored in the Environmental Kuznets Curve hypothesis. In this paper, we introduced a dynamic spatial panel data model approach to account for spatial dependence that is expected to be found with CO_2 emissions and state-level income. We used these two approaches to estimate this spatiotemporal pollution-income relationship—an iterated spatial fixed effects and spatial first difference estimator. Unlike past estimators this procedure is in principal much easier to implement and yields consistent and asymptotically normal

[16] These estimates are based upon the Bhargave-Sargan Approach outlined in Elhorst (2005).

estimates. Additionally, this estimation procedure contributes to the literature by offer standard errors that are robust to heteroskedasticity and serial correlation. Based on the empirical results, we believe that we have relatively compelling evidence that this dynamic spatial panel approach tells a consistent story with expected signs, magnitudes, significant levels, and spatial autocorrelation.

Based upon our empirical results we find evidence that is consistent with the traditional EKC hypothesized inverted-U shaped relationship between CO_2 emissions and income. This inverted-U shaped relationship is found even after controlling for spatial dependence within the data, which seems to offer further support to the purported EKC hypothesis.[17] Unlike past literature, we also find fairly consistent evidence of spatial autocorrelation within the data—these findings imply that CO_2 pollution emissions are not necessarily a local issue. In other words, a neighboring state's CO_2 pollution emissions are potentially affecting a particular state's internal pollution emissions. This insight has tremendous policy implications both at the federal and state level.

According to the recent Copenhagen Treaty, the U.S. is to reduce CO_2 pollution emission by 17% below 2005 levels by 2020. If we are to reach these reduction levels, then the states must adopt regional reduction plans as evidenced by the significant spatial autocorrelation found in this study. The spatial dependence found within in study implies that transboundary pollution associated with CO_2 emissions is potentially a real issue. This regional pollution problem is further complicated by the fact that some states produce fossil fuels while others do not. For example, the state of Georgia's electricity generation and consumption is among the highest in the U.S. despite there being no coal production in the state (coal supplies about half of the electricity output in the state), which means the coal is imported from other states (U.S. Energy Information Administration, 2010). The regional plans to reduce emissions then must inevitably involve energy trading as well as regional regulations to reduce emissions. It is possible that neighboring states may develop cooperative initiatives to reduce emissions which include energy trading

[17] Additionally, it could be argued that the SFD scheme potentially controls for temporal non-stationarity if indeed the first-difference procedure yields difference-stationary processes.

and production. The bottom line is that these regulations or initiatives need to start being developed soon if we are to reduce CO_2 emissions to remain compliant with the 2009 Copenhagen Treaty.

Limitations

One of the drawbacks of the iterated SFE and SFD procedures is that the variance of the spatial autocorrelation parameter, λ, is not estimated because the parameter is determined by a numerical approximation instead of estimated statistically. With a statistical procedure the first and second moments of the autocorrelation parameter can easily be estimated. An estimate of the variance of λ is currently under development by the authors but has not be completed as of yet. Despite our lack of variance estimates, we believe that the other spatial estimation schemes present evidence that emissions are influenced by spatial effects, and therefore the lack of variance estimates does not undermine the results based upon the SFE and SFD procedures.

We faced some significant limitations while conducting this analysis. One of the major obstacles is that there are few if any statistical programs that compute dynamic spatial panel data estimates. The analysis for this work was conducted entirely in Matlab. The SFE and SFD procedures were written by Burnett (2010). The code for the FE and UMLE estimators was obtained from Elhorst's personal website. The code for the Spatial GMM procedure was obtained from Shawn Bucholtz. Stata is working on a written procedure for Cliff-Ord spatial models but the procedure has not been made available to the public as of yet. Piras has developed a library in R for estimating spatial panel data models but does not offer a procedure for dynamic spatial data models.

Finally, the model may be greatly improved by specifying a spatial heterogeneous parameter model as opposed to the homogeneous model we have specified in this analysis. By homogeneity we are implicitly assuming that each state has the same pollution-income relationship (including the shape) on average across time. As our analysis is restricted to the contiguous 48 states this may not be so problematic, but should the analysis be extended to an international study then the homogeneity assumption may prove more problematic. Of course, implementing a heterogeneous dynamic panel model is already problematic because of the incidental parameters problem, so extending the dynamic panel to include heterogeneous spatial dependence may prove to be very difficult. A clustering estimation scheme may be more appropriate for considerations of spatial heterogeneity.

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Appendix

Bias of Elhorst (2003) Fixed Effects Estimator

To demonstrate how Elhorst's FE estimator is biased we follow equations (8) from above:

$$Qy = Qz\gamma + Qu \tag{A.1}$$

$$Qu = \lambda WQu + Q\varepsilon \tag{A.2}$$

where we used the demeaning operator to remove the fixed effect. We can now rewrite (A.1) and (A.2) as

$$(I_{NT} - \lambda W)Qy = (I_{NT} - \lambda W)z\gamma + Q\varepsilon \tag{A.3}$$

Elhorst incorrectly assumes that

$$E(\varepsilon\varepsilon') = \sigma^2 I_{NT}, \tag{A.4}$$

when in actual fact

$$E(\varepsilon\varepsilon') = \sigma^2 Q.^{18} \tag{A.5}$$

Elhorst then constructs a maximum likelihood estimation scheme based upon assumption (A.4). If one tries to correct for assumption in (A.4) by replacing it with (A.5) then the MLE procedure is no longer appropriate because it requires the inverse of *Q* to be calculated. Since *Q* is idempotent its inverse does not exist.[19] Therefore, Elhorst FE estimator is biased.

Iterative Spatial First Difference Estimation Algorithm

Instead of using the demeaning operator to get rid of the fixed effects, one can alternatively first difference the data for (5) and (6) to obtain:

$$\Delta y = \Delta z\gamma + \Delta u \tag{A.6}$$

$$\Delta u = \lambda W\Delta u + \Delta\varepsilon \tag{A.7}$$

Based on first differencing the data, the new algorithm is as follows:

[18] The reader should note that since *Q* is idempotent so $Q'Q = Q$.

[19] The identity matrix is the only idempotent matrix that has an inverse that exists.

1. Compute the OLS residuals from (A.1) to derive $\Delta\tilde{u}$
2. Estimate λ from $\Delta\tilde{u} = \lambda W \Delta\tilde{u} + \Delta\varepsilon$ by using the Newton-Raphson Method to derive $\tilde{\lambda}$.
3. Construct new variables $\tilde{y} = (I_{NT} - \tilde{\lambda}W)\Delta y$ and $\tilde{z} = (I_{NT} - \tilde{\lambda}W)\Delta z$
4. Apply OLS for $\tilde{y}$ on $\tilde{z}$ to yield $\hat{\gamma}$.
5. Construct the new residuals $\hat{\tilde{u}} = \tilde{y} - \tilde{z}\hat{\gamma}$ and return to Step 2 to calculate $\hat{\lambda}$.
6. Construct the robust covariance for $\hat{\gamma}$ by calculating $\hat{A} = \frac{N}{N-K}(\tilde{z}'\hat{\tilde{u}}\hat{\tilde{u}}'\tilde{z})$.

Table 2: Estimation Results for CO_2 Emissions—Income Relationship (Cubic Specification)

			Model Types			
Explanatory Variables	**LSDV**	**Elhorst FE**	**Elhorst UMLE**[20]	**Spatial GMM**	**SFE**	**SFD**
$CO_{2,t-1}$	0.0997*** (14.4799)	0.7925*** (78.3724)	0.9292 (0.0000)	0.6012*** (46.190)	0.2194*** (9.1650)	0.0031 (0.9780)
GDP	18.1054 (0.9896)	16.7154* (1.7678)	-2.8162 (0.0000)	-18.4118 (-0.6029)	-24.5420 (-1.0513)	-46.4511* (-1.7585)
GDP^2	-1.3619 (-0.7526)	-1.5170 (-1.6248)	0.3478 (0.0000)	1.7349 (0.5750)	2.6766 (1.1717)	4.7962* (1.8349)
GDP^3	0.0311 (0.5208)	0.0456 (1.4863)	-0.0135 (0.0000)	-0.0548 (-0.5515)	-0.0963 (-1.2931)	-0.1637* (-1.8994)
CDD	0.0189 (1.0671)	-0.0057 (-0.3110)	0.0113 (0.4300)	-0.0548*** (8.5747)	0.0206 (0.7589)	0.0058 (0.7703)
HDD	0.1029** (2.5205)	-0.0175 (-0.4453)	0.0486 (0.7506)	0.1433*** (7.7373)	0.0424 (0.9065)	0.0835*** (5.1084)
Coal	0.0014*** (9.6629)	0.0002*** (3.2724)	0.0002 (0.9278)	0.0013*** (11.3774)	0.0011*** (4.8702)	0.0009** (2.1506)
Oil	-0.0004 (-1.6262)	0.0001 (0.5816)	0.0002 (0.6093)	0.0018*** (15.8920)	-0.0002 (-0.5777)	0.0005 (1.1047)
λ	N/A	0.9600*** (259.7001)	0.0194 (0.0000)	0.4887*** (11.5029)	0.2089	-0.0188
R^2	0.9288		N/A	0.7967	0.9473	0.5690
Adjusted R^2	0.9266	N/A	N/A	0.7958	0.9471	0.5671
Robust SE	No	No	No	Yes	Yes	Yes

Notes: The numbers in the parentheses denote t-statistics. The superscripts "***", "**", "*" denote a significance level 0.01, 0.05, and 0.10 respectively. LSDV denotes the least squares dummy variable estimate.

[20] These estimates are based upon the Bhargave-Sargan Approach outlined in Elhorst (2005).

Table 3: Estimation Results for CO_2 Emissions—Income Relationship (Distance Based Weighting Matrix)

			Model Types			
Explanatory Variables	**LSDV**	**Elhorst FE**	**Elhorst UMLE**[21]	**Spatial GMM**	**SFE**	**SFD**
$CO_{2,t-1}$	0.1003*** (14.8080)	0.7573*** (71.6389)	0.9295*** (125.2205)	0.5625*** (44.4709)	0.1699*** (8.3233)	0.0028 (0.9937)
GDP	8.5810*** (14.4590)	4.1924*** (11.4810)	1.3646** (2.2207)	1.7146* (1.6515)	7.6260*** (9.6097)	5.1527*** (4.2147)
GDP^2	-0.4196*** (-14.318)	-0.2026*** (-11.2423)	-0.0644** (-2.1378)	-0.0926* (-1.8051)	-0.3741*** (-9.6091)	-0.2393*** (-3.9623)
CDD	0.0189 (1.0665)	-0.0041 (-0.3557)	0.0110 (0.7000)	0.1453*** (13.5900)	0.0109 (0.4803)	0.0084 (1.3508)
HDD	0.1032** (2.5290)	0.0208 (0.7584)	0.0478 (1.2168)	0.1734*** (10.9560)	0.0603 (1.4792)	0.0908 *** (6.3468)
Coal	0.0014*** (9.6936)	0.0006*** (8.9846)	0.0002 (1.5273)	0.0015*** (12.9352)	0.0016*** (6.6061)	0.0010** (2.3367)
Oil	-0.0004 (-1.5871)	0.0007*** (5.2319)	0.0002 (0.9961)	0.0017*** (14.9388)	0.0005 (1.4240)	0.0007 (1.3147)
λ	N/A	0.9480*** (265.9911)	-0.2258 (-1.3118)	0.4206*** (9.8570)	0.0283	-0.0923
R^2	0.9288	0.3996	N/A	0.7761	0.9413	0.5564
Adjusted R^2	0.9266	N/A	N/A	0.7753	0.9411	0.5547
Robust SE	No	No	No	Yes	Yes	Yes

Notes: The numbers in the parentheses denote t-statistics. The superscripts "***", "**", "*" denote a significance level 0.01, 0.05, and 0.10 respectively. LSDV denotes the least squares dummy variable estimate.

[21] These estimates are based upon the Bhargave-Sargan Approach outlined in Elhorst (2005).