A Spatiotemporal Fixed Effects Estimation of U.S. State-Level Carbon Dioxide Emissions

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1. Introduction

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? Ones 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 countrys economy develops over time.

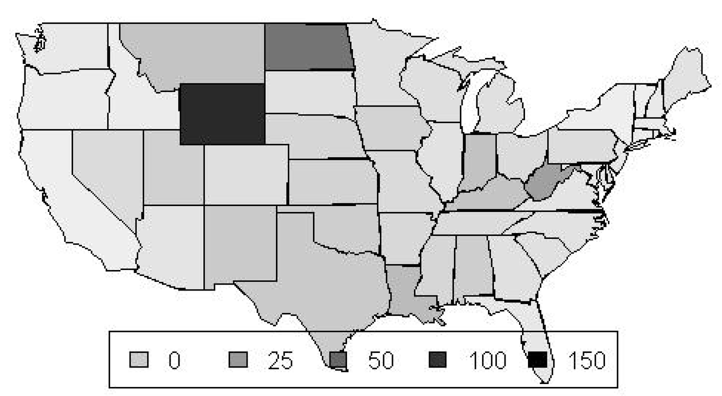

Figure 1: *This figure displays US state-level, per-capita CO_2 for 2001 in terragrams (Tg) of CO_2 equivalent*

One of the major shortcommings of past 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 regions emissions are unaffected by events in neighboring regions (i.e., assume there are no transboundary relationship with emissions). 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 (CO_2) emissions and income (GDP) accounting for both the spatial and temporal components within the data. More precisely, we estimate a spatiotemporal panel model using a newly proposed robust, spatial fixed effects model.

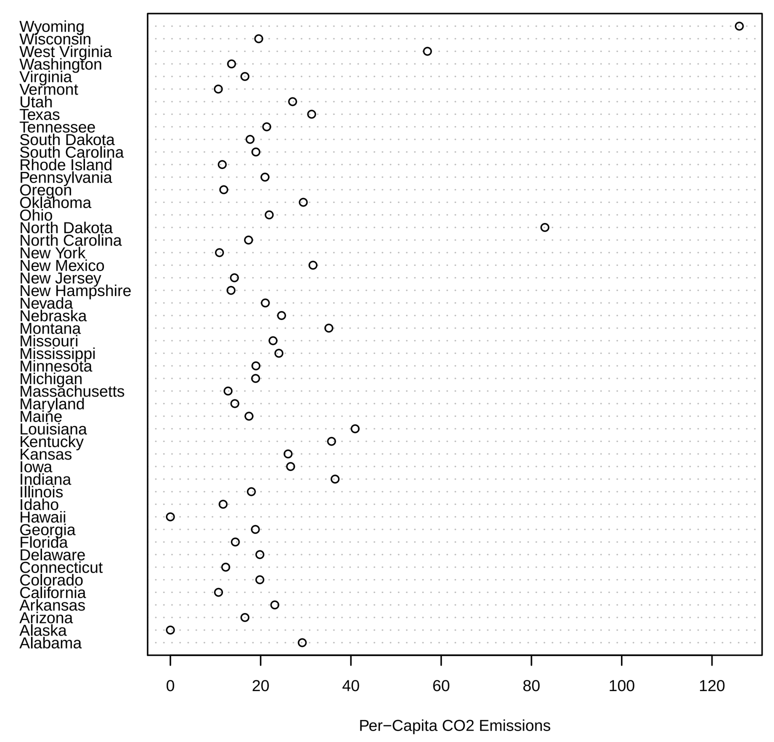

Figure 2: *This figure displays the dot plots of per-capita CO_2 emissions in each state in 2001 in Tg CO_2 equivalent*

2. Data

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. 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. Figures 1 and 2 provide geographic map of state-level, per-capita CO_2 emissions and a count of the same emissions respectively. 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).

3. Methodological Approach

To estimation the pollution-income relationship we can either specify a standard panel estimation scheme or a dynamic panel which includes a lag of the dependent variable on the RHS. The standard panel model is specified as

$$y_t = X_t\beta + \mu_i + \eta_t + u_t, \qquad (1)$$

where μ_i denotes the fixed effect, η_t denotes a time trend, X_t denotes an (*N* x *K*) matrix of explanatory variables including GDP, and β denotes an (*K* x *1*) vector of coefficients on the explanatory variables. The subscript t denotes time; a subscript i for each state has been suppressed for expositionary purposes. Alternatively, the dynamic panel model is specified as

$$y_t = \rho y_{t-1} + X_t\beta + \mu_i + \eta_t + u_t, \qquad (2)$$

where ρ is the coefficient on the lag of the dependent variable on the RHS. The dynamic specification controls for temporal dependence within the CO_2 variable. We move beyond the traditional EKC explanation by positing that local state emissions are affected by neighboring state emissions. We model the transboundary relationship as follows

$$u_t = \lambda W u_t + \epsilon_t, \qquad (3)$$

where λ is the spatial autocorrelation coefficient on the spatial weighting matrix *(*W) and ϵ_t is white noise. The spatial weighting matrix is specified *a prior*. One of the simpler specifications is a binary matrix to indicate whether two states share a common border. We define a weighting matrix based upon the inverse distance between state centroids (for a sensitivity analysis we experimented with other weighting specifications and got similar results). The specification of (3) is often refered to as the spatial error model.

If we estimate (1) or (2) without accounting for (3) then the estimates are potentially *inefficient*. To obtain asymptotically efficient estimates we propose an iterated spatial panel estimation procedure. More information about this iterated procedure can be found in Burnett and Bergstrom (2010). This iterated procedure is in principal simpler to compute then the standard spatial econometrics models and it is robust to heteroskedasticity and serial correlation.

4. Results

	Model Types						
Explanatory Variables	**LSDV**	**Elhorst FE**	**Dynamic Elhorst FE**	**SFE**	**SFD**	**Dynamic SFE**	**Dynamic SFD**
$CO_{2,t-1}$	N/A	N/A	0.9706*** (185.852)	N/A	N/A	0.1182*** (3.5021)	0.0036 (0.7865)
GDP	12.6768*** (18.4822)	15.325*** (10.8307)	1.564*** (4.7597)	12.5123*** (4.4893)	5.6676** (2.2663)	9.7176*** (5.1727)	5.3303* (1.9810)
GDP^2	-0.6196*** (-18.4207)	-0.7666*** (-10.992)	-0.078*** (-4.8157)	-0.6112*** (-4.5091)	-0.2685** (-2.1535)	-0.4777*** (-5.2082)	-0.2522* (-1.8834)
CDD	-0.0179 (-0.8664)	0.3222*** (23.0336)	0.0212*** (5.9369)	-0.0175 (-0.2104)	0.0131 (1.0407)	0.0109 (0.2132)	0.0137 (1.0273)
HDD	0.0692 (1.3415)	0.3497*** (16.5263)	0.0277*** (5.4346)	0.0618 (0.3752)	0.1024 (3.4171)	0.1052 (1.0375)	0.1045*** (3.3073)
Coal	0.0015*** (10.1853)	0.0037*** (26.4352)	0.0001*** (2.672)	0.0016* (1.6760)	0.0011*** (1.2924)	0.0015** (2.6017)	0.0011 (1.2189)
Oil	-0.0008*** (-3.1082)	0.0036*** (25.4736)	0.0003*** (9.0636)	-0.0006 (-0.4934)	0.0005 (0.5286)	-0.0001 (-0.1490)	0.0005 (0.5182)
λ	N/A	0.056* (1.7845)	0.02 (0.63)	-0.0150 (0.0000)	0.0071 (0.4538)	0.0324 (0.0000)	0.0075 (0.4578)
R^2	0.9402	0.6028	0.9796	0.6028	0.6019	0.7347	0.7347
Adjusted R^2	0.9371	0.5894	0.9789	0.5932	0.5934	0.7291	0.7289
Robust SE	No	No	No	Yes	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. Parentheses for spatial autocorrelation coefficient (λ) represent chi-squared statistics determined by Burridge's LM test.

Table 1: *Estimation Results for CO_2 Emissions-Income Relationship (Quadratic Specification) with Distance-Based Spatial Weighting Matrix*

Table 1 provides our estimation results. For a sensitivity analysis we provide three other estimation procedures: the Least Squares Dummy Variable (LSDV), a spatial fixed effects estimator (Elhorst FE), and a dynamic fixed effects estimator (Dynamic Elhorst). If the procedure includes a lag of the dependent variable on the RHS as in (2) then the estimator is dynamic, otherwise it is a standard panel or longitudinal estimator. SFE and SFD in columns 5 and 6 denote our spatial fixed effects and spatial first-difference iterated procedures respectively. Columns 6 and 7 present dynamic versions of these iterated procedures. The variables (listed in column one) include a quadratic specification of GDP, cooling degree days (CDD), heating degree days (HDD), state-level coal production (coal), and state-level oil production (oil). λ denotes the spatial autocorrelation coefficient. Since the SFE, SFD, Dynamic SFE, and Dynamic SFD do not estimate the standard error estimates we provide the p-values based upon Burridge's (1980) Lagrange multiplier test for spatial dependence within the data–these p-values are highlighted in red.

Looking across the different estimation schemes we find robust evidence for the inverted U-shaped relationship between per-capita CO_2 and per-capita GDP. Coal is statistically significant across all the estimation schemes with the exception of the dynamic spatial first-difference estimator.

If we find evidence that CO_2 and GDP are nonstationary then the estimation procedures could yield spurious results and misspecified *t* and *F* statistics. To test for stationarity we conducted panel unit-roots (not shown) which provided some evidence that CO_2 and GDP are characterized as first-difference, trend stationarity processes (Burnett and Bergstrom (2010). An implication of nonstationary variables is that the first-differencing procedures offer properly specified *t* and *F* tests. The most appropriate estimator depends on whether CO_2 emissions are first-difference or second-difference stationary.

In Figure 3 we offer projections of the pollution-income relationship based upon the estimation results in Table 1. GDP is offered in a log scale. The value of 10.5 in the table is equivalent to approximately $36,000 per-capita income. One will notice the consistency with the peak and general shape of the projections which this seems to offer evidence of asymptotic consistency within our estimation procedures.

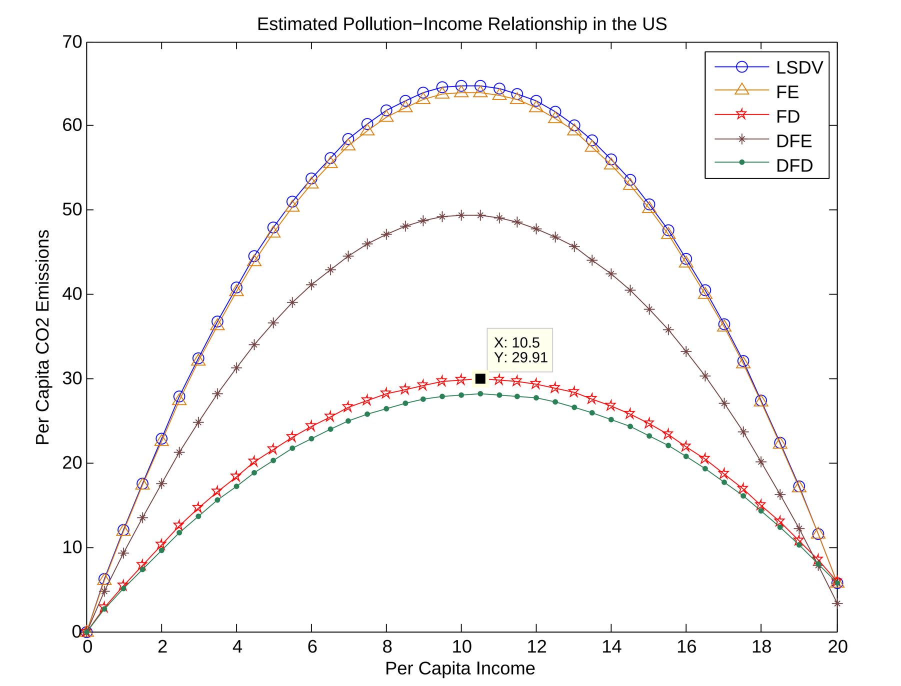

Figure 3: *Projections of estimates based upon results in Table 1*

5. Conclusions and Limitations

Consistent with the EKC hypothesis we find the inverted-U shaped relationship between CO_2 emissions and income. Further, we find adequate evidence that the underlying economic processes driving 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.

One limitation is that λ is estimated numerically so we do not calculate its second moment to perform inference. However, we conducted Lagrange multiplier test (not shown) proposed by Burridge (1980) which offered some evidence in favor of spatial dependence within the data–again the reader is referred to Burnett and Bergstrom (2010).

References

[1] M. Brown, F. Southworth, and A. Sarzynski. *Shrinking the Carbon Footprint of Metropolitan America*, 2008.

[2] W. Burnett and J. Bergstrom. U.S. State-Level Carbon Dioxide Emissions: A Spatial-Temporal Econometric Approach of the Environmental Kuznets Curve. *University of Georgia, Department of Agricultural and Applied Economics, Faculty Series*, 2010.

[3] P. Burridge. On the Cliff-Ord test for spatial autocorrelation. *Journal of the Royal Statistical Society B*, 42: 107-108, 1980.

[4] EPA. National Air Pollutant Emission Trends: 1900-1998 Report. *http://www.epa.gov/*, 2010.

2011 AAEA & NAREA Joint Annual Meeting, 24-26 July 2011, Pittsburgh, PA