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The Effect of Clean Energy Investment on CO_2 Emissions: Insights from a Spatial Durbin Model*

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Abstract

We estimate the direct and indirect effects of clean energy investment on carbon emissions using a Spatial Durbin Model fitted to a panel of 72 countries from 2000 to 2018. We find that a 1 percent increase in domestic clean energy investment reduces domestic carbon emissions by approximately 0.05 percent on average, controlling for country characteristics. However, this benefit is offset by a carbon leakage effect, whereby a 1 percent increase in clean energy investment among neighboring countries leads to about a 0.28 percent increase in domestic carbon emissions. This is suggestive of the outsourcing of pollution from one country to another and indicates that ad hoc policies to promote clean energy investment may be ineffective in achieving global emissions abatement. We conclude that a coordinated international policy framework is required to prevent jurisdiction-shopping by polluters.

Keywords: Clean energy investment, CO_2 emissions, Carbon leakage effect, Spatial Durbin model.
JEL: C13, C23, Q54.

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1. Introduction

The adoption of the Paris Agreement in 2016 committed a majority of countries to limit global temperature rises to less than 2°C above pre-industrial levels. Working toward this goal requires deep cuts to greenhouse gas (GHG) emissions around the world. As carbon dioxide constitutes approximately three-quarters of all anthropogenic GHG emissions and 92% of carbon emissions originate from burning fossil fuels (IPCC, 2014; IEA, 2022), accelerating the energy transition from fossil fuels to clean energy[1] is a key element of emissions reduction strategies (Shahbaz et al., 2020; Chen et al., 2022). This has driven a surge in global clean energy investment that has seen approximately sixfold growth since 2004, with clean energy investments exceeding new investment in fossil fuel power generation by a factor of three in 2018 (IRENA, 2022). However, this rapid growth has occurred in the absence of a detailed understanding of either the domestic effects of clean energy investment on carbon emissions or its spatial spillover effects. Our contribution is to provide new evidence on both of these quantities using a spatial panel data model.

A rapidly growing body of literature has studied the impact of energy investment on emissions abatement, but no consensus has yet emerged. Recent work in this area includes Ganda (2018), Huang et al. (2021), Li and Li (2020), Ma et al. (2021), Mahesh and Shoba Jasmin (2013), Shen et al. (2021), Shahbaz et al. (2020), Wang et al. (2020) and Zhang et al. (2021). One strand of the literature argues that investment in the energy sector can reduce carbon emissions by optimizing the energy structure and improving low-carbon technologies (Ganda, 2018; Ma et al., 2021; Wang et al., 2020; Huang et al., 2021; Shen et al., 2021). An alternative strand argues that gains in energy efficiency fueled by investments in the energy sector can induce a 'rebound effect' of the type described by Jevons (1866) in his famous book *The Coal Question*, which either partially or completely offsets the

[1]Clean energy is defined as energy the consumption of which produces zero carbon dioxide (Lee, 2013). It consists of hydropower and renewable energy resources.

reduction in energy use, potentially exacerbating carbon emissions (Qiu et al., 2019; Deng and Newton, 2017; Li and Li, 2020).

This literature suffers from two important limitations. First, most studies concentrate on the impact of general energy investments on carbon emissions, without distinguishing between clean and dirty energy investments. This approach implicitly sets aside the possibility that investments in clean and dirty energy may affect carbon emissions in different ways. There is reason to believe that this is not an innocuous assumption. For example, Acemoglu et al. (2016) show that investments in dirty technology lead to a relative advantage of dirty technology over clean technology, prohibiting the transition of an economy towards clean technology. Consequently, the failure to distinguish between investments in clean and dirty energy can lead to misleading or biased results.

Second, the geographical coverage of existing empirical studies is limited, with many papers focusing on individual countries. This is problematic given the clear positive spatial correlation of carbon emissions demonstrated in Figure 1, where high-high and low-low agglomerations are easily seen. These agglomerations indicate that initiatives that curtail emissions in one country—including clean energy investments—can have effects that are felt among neighboring countries. Furthermore, Shahnazi and Dehghan Shabani (2020) argue that clean energy investments are spatially correlated due to the prevalence of knowledge spillovers and because neighboring countries often have similar clean energy potential, meaning that clean energy projects initiated in one country can serve as prototypes for similar initiatives in neighboring countries. Consequently, to understand the global impacts of clean energy investment, it is necessary to properly account for spatial dependence.

— Insert Figure 1 Here —

We address both of these problems by fitting a Spatial Durbin Model (SDM) relating carbon dioxide emissions to clean energy investment and a raft of country characteristics using a large panel data set covering 72 countries over the period 2000 to 2018. The SDM not only corrects the estimation bias that would arise from ignoring the spatial correlation in the data, but it also allows us to estimate the domestic effect and the spatial spillover effect of clean energy investments on carbon emissions.

We make two key findings. First, clean energy investment is conducive to local carbon emission mitigation. Specifically, we find that a 1 percent increase in a country's clean energy investment results in approximately a 0.05 percent reduction in domestic carbon emissions. Second, investment in clean energy among neighboring countries tends to exacerbate local carbon emissions. This is evidence of *carbon leakage*, whereby economic activities that generate substantial carbon emissions are relocated from countries seeking to improve their domestic environment (as reflected by their clean energy investment) to neighboring countries with weaker environmental protections (Gray and Shadbegian, 1998; Liao et al., 2018). We further investigate this effect using an auxiliary model of the spatial interactions of clean energy investment and dirty energy consumption. Our results show that domestic investment in clean energy reduces domestic per capita dirty energy consumption, but that investment in clean energy among neighboring countries induces the opposite effect, raising domestic per capita dirty energy consumption.

We show that our results are robust to a range of specification changes. First, we use the geographic distance between country pairs to construct our baseline weighting matrix. Next, we consider alternative spatial weights matrices based on the GDP-adjusted measure of geographical distance and the five-nearest-neighbors. We then construct a convex combination weighting scheme using the previous three weight matrices (Debarsy and Lesage, 2018). Our key findings are robust across all specifications. We also obtain qualitatively similar results when we re-estimate the SDM with lagged explanatory variables to eliminate potential endogeneity issues arising from spatial feedback effects. Lastly, by re-estimating the SDM for subsamples of countries grouped by income level, we show that our principal findings exist for both high-income countries and middle-income countries.

Our results have an important policy implication. Given the evidence that clean energy investment can contribute to domestic carbon abatement efforts, national governments should continue to support clean energy projects in pursuit of their domestic decarbonization goals. However, the evidence of adverse spatial spillover effects arising from clean energy investment means it is unlikely that ad hoc country-specific initiatives will be sufficient to achieve global decarbonization goals. We conclude that global decarbonization will require collective action from governments to create common environmental protection policies that effectively prevent carbon leakage.

The remainder of this article proceeds as follows. In Section 2, we introduce and scrutinize our dataset and lay out our econometric methodology. In Section 3, we present our main empirical findings accompanied by the results of a raft of robustness tests. We conclude and draw out the policy implications of our work in Section 4. Additional details are collected in the Appendix.

2. Methodology and Data

2.1. Spatial Econometric Model

To capture the spatial spillover effects of clean energy investment on carbon emissions, we adopt the SDM developed by Elhorst (2010). The SDM is a popular spatial model that is more general than either the spatial autoregressive (SAR) model or the spatial error model (SEM). In the spirit of LeSage and Pace (2009) and You and Lv (2018), our baseline specification of the SDM is as follows:

$$\begin{aligned}\log CO_{2,it} = \alpha + \rho \sum_{j=1}^{N} w_{ij} \log CO_{2,jt} + \beta_1 \log cei_{it} + \sum_{k=2}^{M} \beta_k \log Z_{it}^{k} + \gamma_1 \sum_{j=1}^{N} w_{ij} \log cei_{jt} \\ + \sum_{k=2}^{M} \gamma_k \sum_{j=1}^{N} w_{ij} \log Z_{jt}^{k} + \mu_i + \eta_t + \varepsilon_{it}, \qquad (1)\end{aligned}$$

where spatial units (countries) are indexed by $i, j = 1, \ldots, N$ and time is indexed by $t = 1, \ldots, T$. The variable names are interpreted as follows: $\mathrm{CO}_{2,it}$ denotes CO_2 emissions per capita, cei_{it} represents clean energy investment and $\{Z_{it}^k\}_{k=2,\cdots,M}$ are a set of control variables defined in Subsection 2.2.1. The spatial weight for the $\{i, j\}$th country-pair—that is, the $\{i, j\}$th element of the spatial weights matrix, $\boldsymbol{W}$—is denoted by w_{ij}. The spatial autoregressive coefficient, denoted by ρ, captures the intensity of the contemporaneous spatial correlation between carbon emissions in neighboring countries and carbon emissions in country i. Lastly, μ_i and η_t denote individual and time fixed effects, respectively, while $\varepsilon_{it} \overset{i.i.d.}{\sim} N(0, \sigma^2)$ is an independent and identically distributed error term with zero mean and variance σ^2, that is commonly assumed to follow an asymptotic normal distribution.

2.1.1. Decomposition of Direct and Indirect Effects

Unlike the parameter estimates obtained from non-spatial models, the coefficients of the SDM cannot be interpreted as marginal effects because of the presence of spatial dependence, which can induce a feedback effect (LeSage and Pace, 2009). Instead, it is common to decompose the estimated coefficients into direct and indirect effects. Referring to Elhorst (2014), we can rewrite the SDM in (1) as follows:

$$\boldsymbol{Y}_t = (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} (\boldsymbol{X_t \beta} + \boldsymbol{W X_t \gamma}) + \boldsymbol{R}_t, \tag{2}$$

where Y_t denotes the dependent variable (CO_2); X_t represents the independent variables, including clean energy investment (cei) and the other control variables ($\mathbf{Z_{it}}$), and $\boldsymbol{R}_t$ collects the remaining terms, including the constant and the error term.

The matrix of partial derivatives of the expected value of $\boldsymbol{Y}_t$ with respect to the k_{th} independent variable of $\boldsymbol{X_t}$ in unit 1 up to unit N at time t is given by:

$$\left[\frac{\partial E(\boldsymbol{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\boldsymbol{Y})}{\partial x_{Nk}}\right]_t = (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\gamma_k & \cdots & w_{1N}\gamma_k \\ w_{21}\gamma_k & \beta_k & \cdots & w_{2N}\gamma_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\gamma_k & w_{N2}\gamma_k & \cdots & \beta_k \end{bmatrix}$$

$$= (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} (\beta_k \boldsymbol{I}_N + \gamma_k \boldsymbol{W}). \tag{3}$$

The direct effect is calculated as the average of the diagonal elements from the matrix $(\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} (\beta_k \boldsymbol{I}_N + \gamma_k \boldsymbol{W})$ and represents the average effect of a unit change in an explanatory variable in a country on the dependent variable. The indirect effect, also known as the spillover effect, is the average of row sums of the off-diagonal elements of the matrix. The indirect effect can be interpreted as the impact on a country's dependent variable as a result of a unit change of a particular independent variable in all other countries. The sum of the direct effect and the indirect effect is the total effect.

It is worth noting that the direct effect of a given independent variable differs from the point estimate $\hat{\beta}$ in (1) due to the feedback effect—that is, the effect of passing through neighboring countries and returning to the country of origin (e.g. passing from country $i \to j \to i$ or passing from country $i \to j \to k \to j \to i$).

2.1.2. Spatial Weights Matrix

The choice of an appropriate spatial weights matrix is important, as different weighting schemes may capture distinct spillover channels (LeSage and Pace, 2009). We use the Geographical distance to construct our baseline spatial weights matrix. (Tobler, 1970) argues that spatial correlations fall as the geographical distance between countries rises. To capture spatial correlations that decay increasingly rapidly with distance, we specify an inverse squared distance matrix (see, for example, You and Lv, 2018). The elements of the weight matrix are defined as follows:

$$w_{ij} = \begin{cases} 1/d_{ij}^2 & i \neq j \\ 0 & i = j \end{cases}, \tag{4}$$

where d_{ij} represents the geographical distance between countries i and j.

We follow standard practice and apply a row-sum normalization such that all rows sum to unity.

2.2. Variables and Data

2.2.1. Variable Selection

The dependent variable in (1) is the level of per capita CO_2 emissions in country i. The independent variable of primary interest is clean energy investment (*cei*). According to Chen et al. (2021), installed clean energy capacity can be used as a proxy for clean energy investment. Consequently, we measure clean energy investment using the installed capacity of solar energy, wind energy, hydropower, bioenergy, geothermal energy and marine energy resources.

In line with previous studies, we control for the following variables gathered in the vector $\{Z_{it}^k\}$ in (1):

(1) Economic Development (*gdp*). We use GDP per capita quoted in constant prices in 2010 US dollars to measure the level of economic development of a country. Grossman and Krueger (1991) show that the nexus between the level of economic development of a country and the level of pollution is characterized by an inverted U-shaped curve, known as the *Environmental Kuznets Curve* (EKC). The curvature arises because environmental quality initially deteriorates with economic growth. However, once a certain level of economic development is reached, the relationship reverses, such that

economic growth acts to curb pollution. To account for the EKC, we include both the level and square of real GDP per capita in our regression model.

(2) Population Density (*pd*). We measure the population density of a country using the proportion of the mid-year total population per unit area. The existing literature identifies two effects linking population density and pollution: a scale effect and an agglomeration effect. The scale effect shows densely populated regions have more demand for goods and services, thereby generating increased CO_2 emissions (Alam et al., 2020). By contrast, the agglomeration effect that may be conducive to CO_2 emissions abatement through economies of scale, cost savings, and technology spillover effects (Jia et al., 2021). For instance, Yi et al. (2022) notes that population agglomeration may enhance technological innovation and improve production efficiency, ultimately reducing carbon emissions. Moreover, high population density areas may be accompanied by raised environmental awareness, increasing the pressure to enact strict environmental regulations and mitigate CO_2 emissions (Selden and Song, 1994; Jiang et al., 2018).

(3) Trade Openness (*trade*). The proportion of imports and exports in GDP is widely used as a measure of trade openness. Theoretically, trade openness may affect the environment in three ways, via scale, technique and structure effects (Grossman and Krueger, 1991). The scale effect suggests a positive link between trade openness and CO_2 emissions, as higher levels of trade openness may expand the scale of production. The technique effect, meanwhile, suggests a negative link between trade and CO_2 emissions via the adoption of improved production technologies. Lastly, the structure effect relates to the effect of trade openness on emissions via changes in the industrial structure. This may act either to worsen or improve emissions.

(4) Urbanization Level (*urban*). The share of the urban population in the total population is adopted to measure the urbanization level in a given country. A strand

of studies found that higher urbanization will increase CO2 emissions due to the rising demand for energy from the increase in urban population, the rapid growth in private transportation and public infrastructure and the industrial concentration around cities (Joshi and Beck, 2018; Zhang and Lin, 2012; Zhang et al., 2018). However, other literature points out that urbanization provides opportunities to achieve economies of scale in using energy more efficiently and managing pollution with lower cost (Martínez-Zarzoso and Maruotti, 2011). As a result, the effect of urbanization on CO_2 emissions is inconclusive.

(5) Industrialization Level (*industry*). We use the ratio of industry value added to GDP as a proxy for the industrialization level. Industrialization leads to more industrial activities and thus generates more CO_2 emissions. This positive link between industrialization and emissions has been confirmed by empirical studies (Huang et al., 2020; Zhang and Lin, 2012; You and Lv, 2018; Rios and Gianmoena, 2018).

2.2.2. Data Sources

We estimate our model using annual data over the $T = 19$ years from 2000 to 2018, inclusive, on the following $N = 72$ countries: Algeria, Argentina, Armenia, Australia, Austria, Belarus, Belgium, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, Kenya, Latvia, Lebanon, Lithuania, Luxembourg, Malaysia, Mexico, Moldova, Morocco, Netherlands, New Zealand, Norway, Panama, Peru, Philippines, Poland, Portugal, Romania, Russia, Serbia, Singapore, Slovak Republic, Slovenia, South Korea, Spain, Sir Lanka, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, and Vietnam.

We obtain data on CO_2 emissions per capita, real GDP per capita, population density, trade openness, urbanization and industrialization from the World Development Indicators (WDI) published by the World Bank. We also source the dirty energy consumption data from the Energy Information Administration (EIA) and the total population from WDI to generate per capita dirty energy consumption (*dcpc*) for use in a subsequent regression model. Finally, data on clean energy investment is obtained from the International Renewable Energy Agency (IRENA).

Detailed definitions of each variable are reported in Table A.1 in Appendix A. The data are logged prior to estimation. In Table 1, we report a range of common descriptive statistics for the natural log of each variable.[2]

— Insert Table 1 Here —

3. Estimation Results

3.1. Spatial Dependence Test

We begin by testing for evidence of spatial dependence in the data. In Table 2, we examine the spatial autocorrelation of CO_2 emissions and clean energy investment using Moran's 1950 I-statistic.[3] We report the global Moran's I statistic for every year between 2000 and 2018, as well as the average over that period. It can be seen that all test statistics are positive and statistically significant at least 5% level, providing overwhelming evidence of positive global spatial dependence in CO_2 emissions and clean energy investments. This implies that economies with high (resp. low) values of CO_2 emissions and clean energy investment are spatially clustered, which motivates the use of spatial econometric techniques.

— Insert Table 2 Here —

[2]We also conduct cross-sectional dependence tests, the panel unit root tests and panel cointegration tests and report the results in Table A.2, A.3 and A.4 in Appendix A, respectively.

[3]Global Moran's $I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{s^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$, where x_i and x_j are the observed values in the ith and jth spatial units, respectively, with $i \neq j$, $\bar{x}$ is the mean of x, w_{ij} is the $\{i,j\}$th element of the spatial weights matrix and $s^2 = n^{-1}\sum_{i=1}^{n}(x_i-\bar{x})^2$ is the sample variance.

To visually illustrate the local spatial dependence in the neighborhood around each observation, Figure 2 shows Moran's I scatter plots for CO_2 emissions and clean energy investment in 2000 and 2018 using our spatial weights matrix. The first and third quadrants indicate spatial concentrations of similar values (i.e. high-high and low-low agglomerations). By contrast, the second and fourth quadrants show the spatial concentration of dissimilar values (i.e. high-low and low-high agglomerations). As shown in Figure 2, in the majority of cases, we observe positive spatial correlation.

— Insert Figure 2 Here —

3.2. Full-sample Estimation Results

To examine whether the SDM is an appropriate choice of model, we conduct several specification tests following Elhorst (2014). The results are summarized in Table 3. First, we use likelihood ratio (LR) tests to determine the appropriate specification of the fixed effects in the SDM. The test results in the first two rows of Table 3 favor a model with both spatial and time-period fixed effects. Next, we perform both the classic Lagrange Multiplier (LM) spatial lag and spatial error tests and their robust counterparts (Anselin et al., 2008; Debarsy and Ertur, 2010) and report the results in the third to sixth rows in Table 3. These tests evaluate whether a traditional non-spatial panel data model fails to capture relevant spatial interactions within the data—specifically, whether a model with spatial lags of the dependent variable or a spatially autocorrelated error term would be preferable to the non-spatial model. We can see that every null hypothesis is rejected at the 1% level of significance, supporting the use of the spatial model over a non-spatial panel data specification.

— Insert Table 3 Here —

In the seventh and eighth rows of Table 3, we test whether the SDM specification can be reduced to either the SAR or SEM specifications using the Wald spatial lag and spatial error tests. The results show that the null hypothesis is rejected at the 1% level of significance, providing strong support for the SDM specification. Consequently, the preferred specification is the SDM with both spatial- and time-fixed effects.

We next access whether a fixed-effects model or a random-effects model is appropriate for the SDM. The estimation results are shown in Table 4. Most of the results are consistent for both models in terms of magnitude and sign. The spatial autoregressive coefficient, ρ, is positive and highly statistically significant, reflecting the positive spatial dependence of CO_2 emissions visible in Figure 2. We perform the Hausman (1978) specification test and reject the null hypothesis at the 1% level of significance, indicating a rejection of the random effects specification in favor of the fixed effects model.

— Insert Table 4 Here —

Because the point estimates of the SDM coefficients cannot be interpreted as marginal effects, we report the direct and indirect effects described in subsection 2.1.1 in Table 5 accompanied by t-statistics obtained by bootstrapping.

— Insert Table 5 Here —

A close examination of Table 5 reveals several important findings. First, consider the direct effects. The variable of primary interest is the log of clean energy investment, $\log cei$. We find that a 1% increase in domestic clean energy investment results in a fall of approximately 0.05% in domestic carbon emissions. This direct effect is statistically significant at the 1% level and is consistent with the finding of Wang et al. (2020) that clean energy investments are conducive to the mitigation of domestic CO_2 emissions.

Regarding the control variables, the estimated parameter on the $\log gdp$ is positive and significant, whereas its squared term is statistically insignificant, which indicates that an inverted U-shaped relationship between economic development and carbon emissions implied by the EKC is not supported. Meanwhile, the direct effect of population density on carbon emissions is negative and significant at a 1% level, implying that the agglomeration effect overwhelms the scale effect. This result is in line with Jiang et al. (2018) and shows that more densely populated countries are more likely to reduce local carbon emissions. Moreover, we also find that the coefficient of the trade openness on carbon emissions is negative, which is consistent with the view that trade can bring advanced technology into an economy, improving energy efficiency and mitigating emissions. On the contrary, the direct effects of the urbanization and industrialization on carbon emissions are positive, in line with the findings of You and Lv (2018); Zhang and Lin (2012); Hosseini and Kaneko (2013) that increases in the degree of urbanization and industrialization at a particular country can aggravate the local carbon emissions. These estimated direct effects are statistically significant at the 1% level.

Next, move on to the estimated indirect effects, which capture the spillover effects from neighboring countries onto the CO_2 emissions of country i. The indirect effect of clean energy investment is positive and statistically significant at 1% level. Specifically, a 1% rise in clean energy investment in neighboring countries leads to a 0.278% increase in domestic CO_2 emissions. This result points to a substantial carbon leakage effect, whereby polluting activities are outsourced from countries seeking to improve their domestic environment (as reflected in their investments in clean energy) to neighboring countries. Further analysis of the carbon leakage mechanism will be the focus of subsection 3.3.

Concerning control variables, the parameters of $\log gdp$ and its quadratic term are significantly positive and negative, respectively. This indicates that economic development in the neighboring countries has a nonlinear effect on local CO_2 emissions. For trade openness, it has a positive indirect effect on carbon emissions. This suggests that countries whose neighbors have high levels of trade openness risk becoming "pollution havens", in the sense that the opening up of international trade may result in the offshoring of polluting activities from countries with strict environmental protections to countries with less stringent environmental regulation (Cai et al., 2018; You and Lv, 2018). In contrast, the indirect effect of urbanization on emissions is significantly negative. This is consistent with You and Lv (2018) and Nan et al. (2022) that increases in urbanization in the neighboring countries can alleviate local carbon emissions. As for other remaining control variables, population density and industrialization have no statistically significant spatial spillover effect.

3.3. Further Evidence of the Carbon Leakage Effect

To further explore our finding of a significant carbon leakage effect, we now investigate the spatial interplay between investment in clean energy and the consumption of dirty energy. To this end, we specify a new SDM similar to (1) in which dirty energy consumption per capita, $\log dcpc$, is the dependent variable and clean energy investment is included among the explanatory variables:

$$\log dcpc_{it} = \rho \sum_{j=1}^{N} w_{ij} \log dcpc_{jt} + \beta \log cei_{it} + \boldsymbol{Z_{it}} \boldsymbol{\alpha} + \gamma \sum_{j=1}^{N} w_{ij} \log cei_{jt} + \sum_{j=1}^{N} w_{ij} \boldsymbol{Z_{it}} \boldsymbol{\Phi} + \mu_i + \eta_t + \varepsilon_{it}, \quad (5)$$

where $\boldsymbol{Z_{it}}$ refers to the same matrix of control variables used in (1), $\boldsymbol{\alpha}$ and $\boldsymbol{\Phi}$ are vectors of unknown parameters to be estimated and the remaining terms are interpreted as before. Our measure of dirty energy consumption includes consumption of oil, coal and natural gas. The estimated direct and indirect effects obtained from this model as well as the accompanying bootstrap t-statistics are reported in Table 6.[4]

— Insert Table 6 Here —

[4]We again follow Elhorst (2014) and conduct an array of tests to identify the correct model specification. The results are reported in Table A.5 in the Appendix.

As can be seen in Table 6, we find that the direct effect of clean energy investment on dirty energy consumption per capita is negative, while the indirect effect is positive. This indicates that domestic investment in clean energy reduces domestic dirty energy consumption per capita but that clean energy investment among a country's neighbors tend to induce the opposite effect. These differing local and regional effects can be explained intuitively. Clean energy investment may promote domestic emissions abatement by scaling up local clean energy production, leading to a substitution away from dirty energy. Additionally, investment in clean energy may arise in response to domestic environmental regulations and incentives, which may, in their own right, lead to reducing dirty energy consumption. Meanwhile, the adverse spatial spillover effect may arise through a simple supply and demand effect, as the decline in dirty energy consumption in one country may depress the price of dirty energy on the regional/global market, stimulating the demand for dirty energy in other countries and contributing to higher carbon emissions (Arroyo-Currás et al., 2015). Consequently, our results indicate that an increase in clean energy investment in one country may lead to the offshoring of polluting activity to neighboring countries with looser environmental controls.

3.4. Robustness Tests

In this section, we test the robustness of our estimation results for (1) in three ways: (i) by lagging the explanatory variables to counter any endogeneity concerns; (ii) by subsampling to test for evidence of income heterogeneity; and (iii) by using different spatial weight matrices.

3.4.1. Lagged Explanatory Variables

In the same vein as Xu et al. (2021) and Wang and Zhu (2020), we re-estimate the SDM, having lagged all of the explanatory variables by one period to eliminate any endogeneity arising from spatial feedback effects. The direct and indirect effects from the lagged specification are reported in Table 7. Our key finding that clean energy investment exerts a negative direct effect and a positive indirect effect on carbon emissions is robust to this change, although the magnitude of the direct effect is smaller in the lagged case. The estimated direct and indirect effects of the control variables are qualitatively similar to the baseline case, although the evidence in favour of direct effect of trade openness on carbon emissions is weakly positive. Overall, therefore, we conclude that our key findings are not compromised by endogeneity among the most explanatory variables.

— Insert Table 7 Here —

3.4.2. Heterogeneity by Income Level

The effects of investments on carbon emissions may vary depending on income levels because of the high cost of clean energy deployment. In order to test for evidence of a heterogeneous income effect, we classify the 72 countries in our sample into high-income and middle-income groups using the World Bank's income group classification for 2021. Based on this classification, we create a dummy variable H equal to one if the country is in the high-income group and zero otherwise. By adding the interaction term between this dummy variable and both the clean energy investment variable and its spatially lagged counterpart into our baseline SDM specification (1), we are able to examine the effects of clean energy investment on carbon emissions at different income levels.

— Insert Table 8 Here —

Table 8 reports the direct and indirect effects of the heterogeneity analysis.[5] First, it is interesting to note that the estimated direct and indirect effects of *logcei* are similar to those reported in Table 5. Given that the direct and indirect effects for the interaction terms

[5] Full estimation results for the SDM, including the interaction terms, are presented in Tables A.6 in the Appendix.

are considerably smaller in magnitude than those associated with *logcei* and insignificant, we conclude that our main estimation results still hold after controlling for the income level. Concerning the remaining control variables, both direct and indirect effects are very consistent with those in Table 5 regarding sign, size and significance, which further ascertains the robustness of our results.

Interestingly, we do not observe significant heterogeneity between the two groups of countries. Clean energy investment has a similar direct emissions abatement effect in high-income and middle-income countries. The indirect effects of clean energy investment on emissions are identical irrespective of whether neighboring countries are in the high-income or middle-income group.

3.4.3. Different Spatial Weight Matrices

We replace the inverse squared distance matrix with economic geography weight, the five-nearest-neighbors weight and convex combination weight in turn. This design helps to eliminate the estimation bias results from the choice of spatial weight matrix.

1. Economic geography. In addition to geographical distance, economic connections among countries also play an important role in determining spatial correlations. For example, countries with similar levels of economic development may share stronger economic connections, leading to stronger spatial correlation. However, economic connections can often be asymmetric between countries. For instance, a developed country may have a stronger economic influence on its neighbors than a developing country. Consequently, we construct an asymmetric economic geography weights matrix that combines geographical distance and relative economic mass in a similar manner to Parent and LeSage (2008) as follows:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}^2} \frac{\overline{gdp_j}}{\overline{gdp_i}} & i \neq j \\ 0 & i = j \end{cases} \tag{6}$$

where $\overline{gdp_k}$ $(k = i, j)$ is country k's average annual GDP per capita over the sample period and d_{ij} is the geographical distance between countries i and j, as above.

2. Five-nearest-neighbors. A popular and simple choice of weights matrix is based on contiguity, where only countries that share a land border are considered neighbors. However, as Maddison (2006) notes, this is problematic if the dataset includes island states with no land borders (e.g. Australia) and can also discount well-known spatial links (e.g. Denmark and Sweden do not share a land border but share strong historical, economic, social and political linkages).[6] A simple way to avoid these issues is to identify the k-nearest-neighbors of each country, regardless of whether they share a land border. Following You and Lv (2018), we set $k = 5$, such that:

$$w_{ij} = \begin{cases} 1 & \text{if } j \text{ is one of } i\text{'s five nearest neighbors} \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

3. Convex combination weight. Although most spatial regression replies on a single traditional weight matrix, a single weight matrix cannot reveal the whole picture of national transnational interaction and cannot account for multiple dimensions of spatial dependence at the same time (Elhorst, 2010; Paci et al., 2014; Nan et al., 2022).[7] To alleviate this issue, following Debarsy and Lesage (2018), we form a

[6] Another common weights matrix defines countries to be neighbors if the distance between their centroids is $< 1,750$ miles. Maddison (2006) points out that this can be problematic for large or oddly shaped countries.

[7] We sincerely thanks an anonymous referee for giving us an excellent suggestion to use the convex

convex combination weight of different spatial matrices as follows:

$$\mathbf{W_c}(\mathbf{\Theta}) = \sum_{m}^{3} \theta_m \mathbf{W_m}, \quad 0 \leq \theta_m \leq 1, \quad \sum_{m}^{3} \theta_m = 1, \tag{8}$$

where $\mathbf{W_1}$, $\mathbf{W_2}$, and $\mathbf{W_3}$ refer to the three spatial weights matrices: inverse distance squared, economic geography and five-nearest-neighbor weights, respectively. As is common practice, all three spatial weights matrices are row-standardized so that $\mathbf{W_c}$ is also row-normalized. $\mathbf{\Theta} = (\theta_1, \theta_2, \theta_3)'$ is the vector containing all parameters of the convex combination. And θs represent the relative importance of different types of spatial dependence. This study estimates the SDM with two-way fixed effects model based on convex combination weight using the Bayesian Markov Chain Monte Carlo (MCMC) approach developed by Debarsy and Lesage (2018).

— Insert Table 9 Here —

We present the direct and indirect effects using the above spatial weights matrices in Table 9. Our key findings of the significantly negative direct and positive indirect effects of clean energy investment on CO_2 emissions are robust across the alternative three spatial weight matrices. Additionally, for other control variables, the direct effects are relatively similar across all three weighting schemes, although some of the indirect effects are weaker when using the five-nearest neighbors weights matrix ($\mathbf{W_3}$). This is likely a result of the greater sparsity of $\mathbf{W_3}$ relative to either of the other weights matrices that we consider.

combination weight to capture different channels of spillover effects.

4. Conclusion and Policy Implications

Investments in clean energy are a key pillar of decarbonization strategies around the world. However, existing research on the nexus between energy investments and carbon emissions has largely failed to distinguish between clean and dirty energy investments and to account for the spatial dependence in the data. We address both of these issues by fitting a spatial panel data model to a large panel data set covering 72 countries over the 19 years from 2000 to 2018.

Our results indicate that investments in clean energy in a given country can be effective in mitigating domestic carbon emissions. However, we find that clean energy investments can generate adverse spillover effects that increase emissions in other countries through a carbon leakage effect, whereby increased investment in clean energy in one country leads to the offshoring of polluting activity to neighboring countries with less stringent environmental protections. Such countries risk becoming pollution havens in the absence of international regulation to prevent jurisdiction-shopping on the part of polluters.

Our results have several policy implications. First, given the evidence that clean energy investments can contribute to domestic emissions reduction, national governments should continue to support clean energy investment in order to make progress toward their decarbonization objectives. Second, because of the spatial dependence in global emissions, a free-rider problem may arise that cannot be solved by national policymakers operating alone. Therefore, it is necessary to improve international cooperation, establish a global carbon emissions control mechanism and move from a system dominated by unilateral action to one subject to a higher level of common governance. An important aspect of this will be the introduction of mechanisms to prevent carbon leakage, including border carbon adjustments, consistent pricing of carbon emissions, and levies of consumption taxes for emissions-intensive activities.

We close by noting two important avenues for continuing research. First, due to data limitations, we are obliged to use installed renewable energy capacity to proxy for clean energy investment. This is an imperfect proxy, not least because it involves the use of a stock to proxy for a flow. The development of an improved proxy can be expected to yield more precise estimation results. Second, the use of firm-level data to study the carbon leakage mechanism in detail would provide a firm basis for the development of regulations to prevent jurisdiction-shopping by polluters.

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Table 1: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
$\log CO_2$	1368	1.549	0.823	-1.670	3.245
$\log cei$	1368	8.139	2.006	1.889	13.452
$\log gdp$	1368	9.373	1.199	6.640	11.626
$\log gdp^2$	1368	89.300	22.304	44.091	135.163
$\log pd$	1368	4.309	1.296	0.914	8.981
$\log trade$	1368	4.356	0.533	2.986	6.081
$\log urban$	1368	4.183	0.325	2.901	4.605
$\log industry$	1368	3.275	0.266	2.353	4.076
$\log dcpc$	1368	0.607	0.876	-2.546	2.813

Table 2: Global Moran's I-statistic for CO_2 emission per capita and clean energy investment

Year	$\log CO_2$	$\log cei$	Year	$\log CO_2$	$\log cei$
2000	0.264***	0.214***	2010	0.219***	0.190***
2001	0.272***	0.212***	2011	0.191***	0.170***
2002	0.278***	0.208***	2012	0.174***	0.169***
2003	0.272***	0.212***	2013	0.170***	0.157***
2004	0.264***	0.218***	2014	0.161***	0.152***
2005	0.253***	0.219***	2015	0.165***	0.139***
2006	0.247***	0.216***	2016	0.167***	0.133**
2007	0.229***	0.216***	2017	0.173***	0.135**
2008	0.222***	0.216***	2018	0.173***	0.130**
2009	0.215***	0.205***	Average	0.223***	0.192***

NOTES: The null hypothesis is the absence of global spatial autocorrelation. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3: Model selection

	Tests	**Statistics**	**p-value**
(1)	LR spatial fixed effects	4406.97	0.000
(2)	LR time fixed effects	290.28	0.000
(3)	LM spatial lag	615.048	0.000
(4)	LM spatial error	849.557	0.000
(5)	Robust LM spatial lag	23.834	0.000
(6)	Robust LM spatial error	258.362	0.000
(7)	Wald spatial lag	437.055	0.000
(8)	Wald spatial error	30.110	0.000

Table 4: SDM estimation results for the full sample

Variables	Fixed Effects Model	Random Effects Model
$\log cei$	-0.060***	-0.060***
	(-7.472)	(-7.723)
$\log gdp$	0.300*	0.329**
	(1.886)	(2.094)
$\log gdp^2$	0.003	0.003
	(0.410)	(0.313)
$\log pd$	-0.197***	-0.197***
	(-16.100)	(-16.822)
$\log trade$	-0.116***	-0.140***
	(-4.028)	(-5.102)
$\log urban$	0.969***	0.937***
	(17.463)	(17.257)
$\log industry$	0.271***	0.232***
	(5.221)	(4.651)
$W * \log cei$	0.087***	0.067***
	(5.496)	(5.919)
$W * \log gdp$	0.529*	-0.360**
	(1.757)	(-2.048)
$W * \log gdp^2$	-0.043***	0.002
	(-2.704)	(0.193)
$W * \log pd$	0.199***	0.202***
	(8.865)	(12.962)
$W * \log trade$	0.205***	0.211***
	(3.958)	(4.941)
$W * \log urban$	-1.014***	-0.974***
	(-9.736)	(-11.903)
$W * \log industry$	-0.243***	-0.281***
	(-2.607)	(-4.034)
ρ	0.879***	0.898***
	(84.683)	(76.431)
Obs.	1368	1368
R^2	0.905	0.894
Hausman Test	89.712	0.000 (p-value)

Notes: t-statistics are shown in parentheses. *, **,*** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Direct and indirect effects

Variables	Direct Effect	Indirect Effect
$\log cei$	-0.051***	0.278***
	(-6.421)	(2.683)
$\log gdp$	0.508***	6.359***
	(13.587)	(3.229)
$\log gdp^2$	-0.007	-0.322***
	(-0.817)	(-3.098)
$\log pd$	-0.190***	0.213
	(-16.993)	(1.546)
$\log trade$	-0.089***	0.841**
	(-3.148)	(2.549)
$\log urban$	0.924***	-1.321**
	(17.373)	(-2.051)
$\log industry$	0.269***	-0.056
	(5.322)	(-0.100)

Notes: t-statistics are shown in parentheses. *, **,*** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Estimated direct and indirect effect: dependent variable is dirty energy consumption per capita

Variables	Direct Effect	Indirect Effect
$\log cei$	-0.039***	0.226**
	(-5.046)	(2.246)
$\log gdp$	0.468***	5.476***
	(2.938)	(2.860)
$\log gdp^2$	-0.006	-0.268***
	(-0.737)	(-2.656)
$\log pd$	-0.113***	0.169
	(-10.340)	(1.257)
$\log trade$	-0.014	0.175***
	(-0.513)	(3.594)
$\log urban$	1.139***	-1.368**
	(21.774)	(-2.166)
$\log industry$	0.114**	-0.068
	(2.295)	(-0.123)

Notes: t-statistics are shown in parentheses. *, **,*** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Robustness to the use of lagged explanatory variables

Variables	Direct Effect	Indirect Effect
$\log cei$	-0.030***	0.377**
	(-3.401)	(2.395)
$\log gdp$	0.595***	-0.873
	(3.052)	(0.266)
$\log gdp^2$	-0.016	0.022
	(-1.623)	(0.131)
$\log pd$	-0.189***	0.021
	(-15.971)	(0.101)
$\log trade$	0.059*	1.120**
	(1.921)	(2.098)
$\log urban$	1.063***	-0.427
	(17.052)	(-0.421)
$\log industry$	0.149***	-0.514
	(2.830)	(-0.553)

Notes: t-statistics are shown in parentheses. *, **,*** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Heterogeneity by income level

Variables	Direct Effect	Indirect Effect
$\log cei$	-0.050***	0.266***
	(-6.275)	(2.662)
$\log cei \times H$	-0.002	-0.026
	(-0.327)	(-0.525)
$\log gdp$	0.517***	6.076***
	(3.277)	(3.322)
$\log gdp^2$	-0.007	-0.304***
	(-0.851)	(-3.141)
$\log pd$	-0.189***	0.197
	(-16.411)	(1.577)
$\log trade$	-0.089***	0.763**
	(-3.108)	(2.515)
$\log urban$	0.920***	-1.301**
	(16.620)	(-2.182)
$\log industry$	0.269***	-0.068
	(5.346)	(-0.131)

Notes: t-statistics are shown in parentheses. *, **,*** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Robustness to use different spatial weight matrices

	Model 1	Model 2	Model 3
Variables	$\mathbf{W_2}$	$\mathbf{W_3}$	$\mathbf{W_c}$
Panel A: Direct Effect			
$\log cei$	-0.050***	-0.051***	-0.048***
	(-6.182)	(-6.525)	(-6.031)
$\log gdp$	0.425**	0.618***	0.615***
	(2.624)	(3.886)	(3.892)
$\log gdp^2$	-0.002	-0.012	-0.013
	(-0.224)	(-1.470)	(-1.533)
$\log pd$	-0.200***	-0.195***	-0.187***
	(-18.036)	(-18.035)	(-16.562)
$\log trade$	-0.059***	-0.083***	-0.084***
	(-2.088)	(-3.008)	(-2.964)
$\log urban$	0.900***	0.898***	0.915***
	(17.008)	(17.233)	(17.328)
$\log industry$	0.244***	0.251***	0.257***
	(4.789)	(5.020)	(5.122)
Panel B: Indirect Effect			
$\log cei$	0.215***	0.058*	0.140**
	(2.645)	(1.706)	(1.975)
$\log gdp$	5.022***	1.001	4.465***
	(3.059)	(1.537)	(3.194)
$\log gdp^2$	-0.257***	-0.051	-0.231***
	(-3.390)	(-1.488)	(-3.120)
$\log pd$	0.179*	0.062	0.087
	(1.702)	(1.427)	(0.921)
$\log trade$	0.452*	0.196*	0.371
	(1.707)	(1.784)	(1.617)
$\log urban$	-0.773*	-0.288	-0.788*
	(-1.666)	(-1.362)	(-1.769)
$\log industry$	-0.051	0.030	-0.368
	(-0.110)	(0.158)	(-0.891)

Notes: t-statistics are shown in parentheses. *, **,*** represent significance at the 10%, 5%, and 1% levels, respectively. $\mathbf{W_c} = \theta_1\mathbf{W_1} + \theta_2\mathbf{W_2} + \theta_3\mathbf{W_3} = 0.191\mathbf{W_1} + 0.106\mathbf{W_2} + 0.703\mathbf{W_3}$.

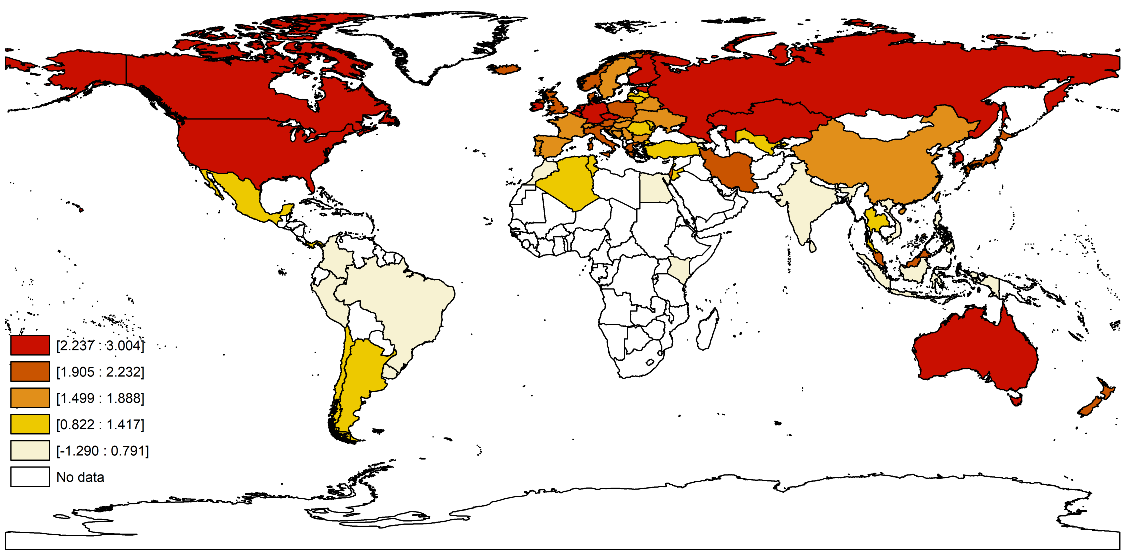
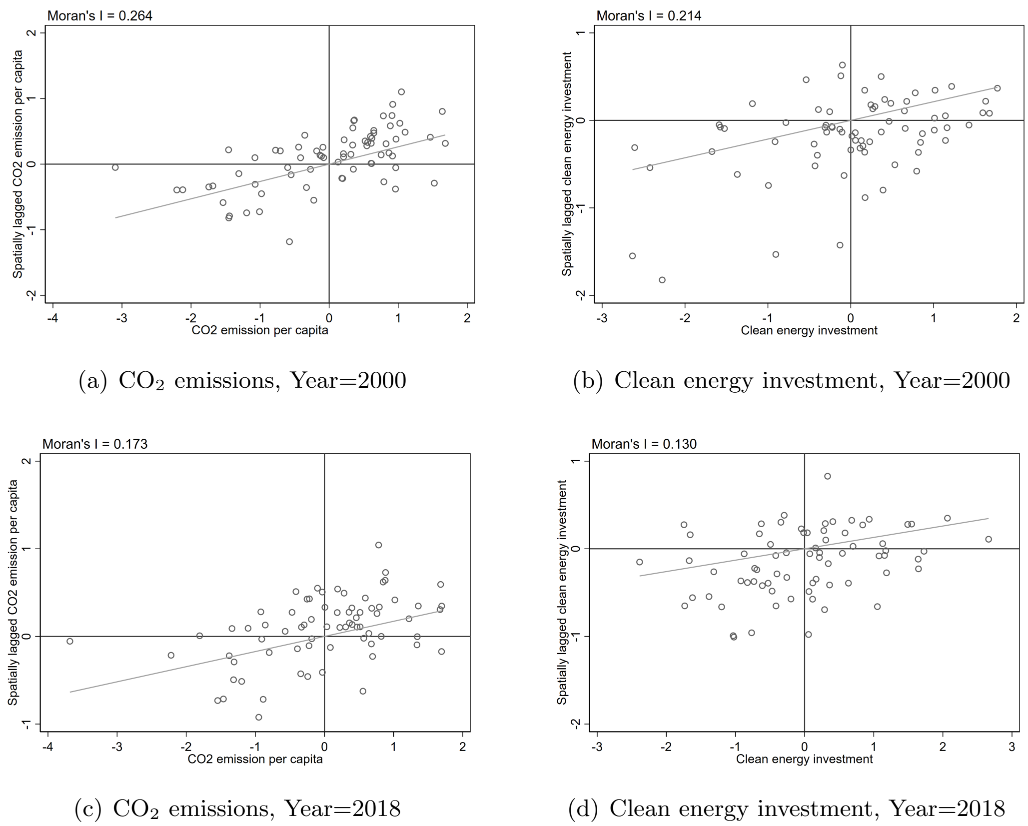


Figure 1: Spatial distribution of the log-arithmetic mean of per capita CO_2 emissions from 2000 to 2018.



(a) CO_2 emissions, Year=2000

(b) Clean energy investment, Year=2000

(c) CO_2 emissions, Year=2018

(d) Clean energy investment, Year=2018

Figure 2: Moran's I scatter plots of the logarithm of per capita CO_2 emissions and clean energy investment in 2000 and 2018.

Appendix A

Table A.1: Variable definitions and data sources

Variables	Definitions	Units	Sources
CO_2 emissions	Carbon dioxide emissions per capita	Metric tonnes/person	WDI
Clean energy investment	Installed renewable energy capacity	Megawatts	IRENA
GDP	Real GDP per capita (base year=2010)	US$/person	WDI
Population density	Mid-year population divided by land area in square kilometers	Person/square kilometers	WDI
Trade openness	Proportion of total exports and imports in GDP	%	WDI
Urbanization level	Proportion of the urban population in the total population	%	WDI
Industrialization level	Percentage of the added value of industry in GDP	%	WDI
Dirty energy consumption per capita	Total energy consumption in coal, oil and natural gas, divided by total population	Tonnes of oil equivalent/person	EIA

Notes: WDI=World Development Indicators; IRENA=International Renewable Energy Agency; EIA=Energy Information Administration.

Table A.2: Cross-sectional dependence tests

Variables	$\log CO_2$	$\log cei$	$\log gdp$	$\log gdp^2$	$\log pd$	$\log trade$	$\log urban$	$\log industry$	$\log dcpc$
CD-test	11.094**	197.638**	175.214***	174.998***	51.817***	36.766***	118.573***	60.886***	9.330***

Notes: The null hypothesis is no cross-sectional dependence. The test statistical follows the normal standard distribution $N(0,1)$. *** represents significance at the 1% level.

Table A.3: Panel unit root tests

Level	**LLC**	**IPS**	**Breitung**	**MW**	**CIPS**
$\log CO_2$	-3.453	3.666	3.382	108.629	2.560
	(0.000)	(1.000)	(1.000)	(0.988)	(0.995)
$\log cei$	2.492	13.719	5.473	87.118	-1.003
	(0.994)	(1.000)	(1.000)	(1.000)	(0.158)
$\log gdp$	-6.276	0.660	2.726	148.731	-1.164
	(0.000)	(0.745)	(0.997)	(0.376)	(0.122)
$\log gdp^2$	-5.190	1.362	2.945	134.672	-0.835
	(0.000)	(0.913)	(0.998)	(0.633)	(0.202)
$\log pd$	-2.446	6.925	-0.392	213.072	-7.380
	(0.007)	(1.000)	(0.348)	(0.000)	(0.000)
$\log trade$	-4.083	-0.102	-0.314	144.694	2.588
	(0.000)	(0.459)	(0.377)	(0.468)	(0.995)
$\log urban$	-50.434	-26.648	-1.240	682.190	7.085
	(0.000)	(0.000)	(0.108)	(0.000)	(1.000)
$\log industry$	-4.114	0.641	-0.325	127.469	-2.113
	(0.000)	(0.739)	(0.372)	(0.835)	(0.017)
$\log dcpc$	-3.736	2.931	3.038	111.748	1.660
	(0.000)	(0.998)	(0.999)	(0.979)	(0.952)
First Difference	**LLC**	**IPS**	**Breitung**	**MW**	**CIPS**
$\log CO_2$	-12.650	-13.034	-11.141	555.683	-9.406
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log cei$	-7.656	-6.198	-6.173	304.604	-4.759
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log gdp$	-11.817	-9.719	-9.387	407.303	-3.753
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log gdp^2$	-12.038	-9.896	-9.417	410.877	-3.492
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log pd$	-12.760	-10.415	-3.253	597.080	-4.175
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$\log trade$	-15.427	-14.722	-10.269	623.416	-5.670
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log urban$	-2.360	-6.764	-3.705	332.734	-1.559
	(0.009)	(0.000)	(1.000)	(0.000)	(0.060)
$\log industry$	-15.582	-14.499	-10.621	630.716	-7.895
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log dcpc$	-12.355	-12.809	-10.708	546.413	-9.235
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Abbreviation: LLC =Levin, Lin, and Chu (2002); IPS= Im, Pesaran, and Shin (2003), Breitung=Breitung (2001); MV=Maddala and Wu (1999), CIPS=Pesaran (2007)

Notes: The p values are in the parentheses. Under the null hypothesis, data are stationary. In all tests, a constant is included, and lag equals one. For IPS test, we exclude Singapore, since its urbanization ratio is equal to 100% since 2000, indicating no within time variation.

Table A.4: Panel cointegration tests

Cointegration Test	AR parameter		Test statistics	p-value
Westerlund Test	Panel Specific	Variance ratio	-3.958	0.000
	Common	Variance ratio	-2.864	0.002
Pedroni Test	Panel Specific	Modified PP t	9.290	0.000
		PP t	-13.319	0.000
		ADF t	-15.515	0.000
	Common	Modified variance ratio	-7.494	0.000
		Modified PP t	6.380	0.000
		PP t	-10.869	0.000
		ADF t	-11.963	0.000

Notes: $\mathbf{H_0}$: No cointegration. Test based on the common AR parameter has the alternative hypothesis that all panels are cointegration; Test based on the panel specific AR parameter has the alternative hypothesis that some panels are cointegration. PP=Phillips–Perron; ADF=Augmented Dickey–Fuller. For Pedroni test under common AR parameter, we exclude Singapore, since its urbanization ratio is equal to 100% since 2000, indicating no within time variation.

Table A.5: Model selection for dirty energy consumption per capita

	Tests	**Statistics**	**p-value**
(1)	LR spatial fixed effects	4376.477	0.000
(2)	LR time fixed effects	288.223	0.000
(3)	LM spatial lag	663.050	0.000
(4)	LM spatial error	911.962	0.000
(5)	Robust LM spatial lag	36.501	0.000
(6)	Robust LM spatial error	285.412	0.000
(7)	Wald spatial lag	484.074	0.000
(8)	Wald spatial error	35.373	0.000
(9)	Hausman test	70.591	0.000

Table A.6: List of Countries Grouped by Income Level

Classification	Country			
High-income	Australia	Austria	Belgium	Canada
	Chile	Croatia	Czech Republic	Denmark
	Estonia	Finland	France	Germany
	Greece	Hungary	Iceland	Ireland
	Israel	Italy	Japan	Latvia
	Lithuania	Luxembourg	Netherlands	New Zealand
	Norway	Poland	Portugal	Singapore
	Slovak Republic	Slovenia	South Korea	Spain
	Sweden	Switzerland	U.K.	U.S.
	Uruguay			
Middle-income	Algeria	Argentina	Armenia	Belarus
	Bosnia and Herzegovina	Brazil	Bulgaria	China
	Colombia	Egypt	Georgia	India
	Indonesia	Iran	Jordan	Kazakhstan
	Kenya	Lebanon	Malaysia	Mexico
	Moldova	Morocco	Panama	Peru
	Philippines	Romania	Russia	Serbia
	Sri Lanka	Thailand	Tunisia	Turkey
	Ukraine	Uzbekistan	Vietnam	