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 73 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 0.19 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 at 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 curb 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 may 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 73 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, clean energy investment in 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 dirty energy consumption but that investment in clean energy among neighboring countries induces the opposite effect, raising domestic dirty energy consumption.

We show that our results are robust to a range of specification changes. We consider three different spatial weights matrices based on the geographic distance between country pairs, a GDP-adjusted measure of geographical distance and the five-nearest-neighbors weighting scheme. Our key findings are robust across all three 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 are robust across both groups but that clean energy investments mitigate carbon emissions more effectively in high-income countries than in 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 an 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:

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

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:

$$\begin{aligned}\left[\frac{\partial E(\boldsymbol{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\boldsymbol{Y})}{\partial x_{Nk}}\right]_t &= (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\gamma_k & \cdots & w_{1N}\gamma_k \\ w_{21}\gamma_k & \beta_k & \cdots & w_{2N}\gamma_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\gamma_k & w_{N2}\gamma_k & \cdots & \beta_k \end{bmatrix} \\ &= (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} (\beta_k \boldsymbol{I}_N + \gamma_k \boldsymbol{W}) \,. \end{aligned} \tag{3}$$

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 consider the following three weights matrices:

1. Geographical distance ($\mathbf{W_1}$). Tobler's (1970) first law of geography states that spatial correlations fall as the geographical distance between countries rises. To capture spatial correlations that decay increasingly rapidly with distance, it is common to

specify an inverse squared distance matrix (see, for example, You and Lv, 2018). The elements of the weights 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.

2. Economic geography ($\mathbf{W_2}$). 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 may 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 weighting matrix that combines geographical distance and relative economic mass in a similar manner to Parent and LeSage (2008). The elements of $\mathbf{W_2}$ are as follows:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}^2} \frac{\overline{gdp_j}}{\overline{gdp_i}} & i \neq j \\ 0 & i = j \end{cases}, \tag{5}$$

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.

3. Five-nearest-neighbors ($\mathbf{W_3}$). 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).[2] 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:

$$w_{ij} = \begin{cases} 1 & \text{if } j \text{ is one of } i\text{'s five nearest neighbors} \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

For each weights matrix, 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

[2] 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.

and Krueger (1991) show that the nexus between the level of economic development of a country and the level of pollution is characterised 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 (*pop*). We measure the population of a country using the mid-year total population estimate. The existing literature identifies two effects linking population and pollution: a size effect and an agglomeration effect. The population size effect reflects how a larger population generates more demand for goods and services, thereby generating increased CO_2 emissions (Alam et al., 2020). By contrast, the population agglomeration effect indicates that population agglomeration may be conducive to CO_2 emissions abatement. Yi et al. (2022) notes that population agglomeration may enhance technological innovation and improve production efficiency, ultimately reducing carbon emissions. Moreover, the growing population may raise environmental awareness, increasing the pressure to enact strict environmental regulations and mitigate CO_2 emissions (Selden and Song, 1994).

(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) Energy Consumption Structure (*ec*). In line with the existing literature, we use fossil fuel consumption as a proportion of total energy consumption to describe the energy consumption structure of a country. Countries that consume a larger share of fossil fuels in their total energy use will generate more carbon emissions than those that consume a larger share of non-fossil fuels (Bai et al., 2020). Consequently, the energy consumption structure as defined here is expected to be positively related to CO_2 emissions.

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 $N = 73$ 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, Saudi Arabia, 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, total population and trade openness from the World Development Indicators (WDI) published by the World Bank. We source data on the structure of energy consumption from the Energy Information Administration (EIA). We also gather data on dirty energy consumption (*dc*) for use in a subsequent regression model from the same source. 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.

— 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] Three sets of results are reported in the table, one corresponding to each spatial weights matrix. In each case, we report the global Moran's I statistic for every year between 2000 and 2018, as well as the average over that period. In every case, the test statistic is positive and statistically significant at the 1% 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 —

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 the spatial weights matrix $\mathbf{W_1}$[4]. The first and third quadrants indicate spatial concentrations of similar values (i.e. high-high and low-low agglomerations).

[3] Global Moran's $I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})\left(x_j-\bar{x}\right)}{s^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$, 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.

[4] Equivalent scatter plots using spatial weight matrices $\mathbf{W_2}$ and $\mathbf{W_3}$ are provided in Figures A.1 and A.2 in Appendix A.

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 summarised in Table 3. In panel A of the table, we use likelihood ratio (LR) tests to determine the appropriate specification of the fixed effects in the SDM. The test results favour a model with both spatial and time-period fixed effects. Next, in the first four rows of panel B, we report results for both the classic Lagrange Multiplier (LM) spatial lag and spatial error tests and their robust counterparts (Anselin et al., 2008; Debarsy and Ertur, 2010). 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. For all three of our spatial weights matrices, every null hypothesis is rejected at the 5% level of significance at least, supporting the use of the spatial model over a non-spatial panel data specification.

— Insert Table 3 Here —

In the fifth and sixth rows of panel B in 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. For all three spatial weights matrices, the null hypothesis is rejected at the 5% level of significance or better, providing strong support for the SDM specification. In the final row of the table, we assess the fixed effects model against a random effects specification using the Hausman (1978) specification test. For all three spatial weights matrices, the null hypothesis is rejected at the 1% level of significance, indicating a rejection of the random effects specification in favour of the fixed effects model. Consequently, the SDM with both spatial and time-period fixed effects is the preferred specification.

In Table 4, we present parameter estimates for the SDM over the full sample (i.e. including all countries). We adopt the geographic distance weighting scheme (matrix $\mathbf{W_1}$) as our benchmark set-up and treat the other two weighting schemes as robustness tests. The robustness of our results across the three spatial weights matrices is striking—the sign, magnitude and statistical significance of the estimated coefficients are very similar in each case. The spatial autoregressive coefficient, ρ, is positive and highly statistically significant in all cases, reflecting the positive spatial dependence of CO_2 emissions visible in Figure 2.

— 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. 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.

— Insert Table 5 Here —

A close examination of Table 5 reveals several important findings. First, consider the direct effects reported in panel A of the table. The variable of primary interest is the log of clean energy investment, *logcei*. We find that a 1% increase in domestic clean energy investment results in a fall of approximately 0.05% in domestic carbon emissions in the benchmark model, with very little sensitivity to the use of alternative weights. This 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.

Moving on to the control variables, the estimated parameters on the level and square of log GDP are indicative of the inverted U-shaped relationship between economic development and carbon emissions implied by the EKC (You and Lv, 2018; Li and Li, 2020; Chen et al., 2022). Meanwhile, the direct effect of 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. By contrast, the direct effect of the energy consumption structure on carbon emissions is positive, in line with the findings of Li and Li (2020) that a higher proportion of fossil fuel consumption in total energy consumption is associated with higher emissions. Each of these estimated direct effects is statistically significant at the 1% level. The only variable for which we obtain an insignificant direct effect is population, which may reflect the countervailing influence of the population size and agglomeration effects on carbon emissions.

Panel B of Table 5 shows 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 the 5% level or better, regardless of which weighting scheme is used. In our benchmark model using geographic distance weights, a 1% rise in clean energy investment in neighboring countries leads to a 0.188% 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.

Most of the remaining control variables have no statistically significant spatial spillover effect. The only exception is trade openness, which we find to have 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).

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, $\log dc$, is the dependent variable and clean energy investment is included among the explanatory variables:

$$\log dc_{it} = \rho \sum_{j=1}^{N} w_{ij} \log dc_{jt} + \beta \log cei_{it} + \boldsymbol{Z_{it}\alpha} + \gamma \sum_{j=1}^{N} w_{ij} \log cei_{jt} + \sum_{j=1}^{N} w_{ij} \boldsymbol{Z_{it}\Phi} + \mu_i + \eta_t + \varepsilon_{it}, \tag{7}$$

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.[5]

— Insert Table 6 Here —

[5] We again follow Elhorst (2014) and conduct an array of tests to identify the correct model specification. The results are reported in Table A.3 in the Appendix.

Regardless of the weighting scheme used, we find that the direct effect of clean energy investment on dirty energy consumption is negative, while the indirect effect is positive. This indicates that domestic investment in clean energy reduces domestic dirty energy consumption 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 two ways: (i) by lagging the explanatory variables to counter any endogeneity concerns; and (ii) by subsampling to test for evidence of income heterogeneity.

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 both direct and indirect effects of trade openness on carbon emissions is weaker. Overall, therefore, we conclude that our key findings are not compromised by endogeneity among the 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 73 countries in our sample into high-income and middle-income groups using the World Bank's income group classification for 2021.[6] 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.

In Table 8, we provide a concise summary of both the direct and indirect effects of *logcei* and $logcei \times H$ on carbon emissions.[7] First, it is interesting to note that the estimated direct and indirect effects of *logcei* are similar to those reported for our baseline specification in Table 5. Given that the direct and indirect effects for the interaction terms are either considerably smaller in magnitude than those associated with *logcei* or insignificant, we conclude that our main estimation results still hold after controlling for the income level.

[6] Table A.2 of Appendix A lists countries in high-income and middle-income groups.

[7] Full estimation results for the SDM, including the interaction terms, are presented in Tables A.4 and A.5 in the Appendix.

Nevertheless, we do observe some interesting heterogeneity between the two groups of countries.

— Insert Table 8 Here —

The direct effect of the interaction term $logcei \times H$ is approximately -0.012 and is statistically significant at the 5% and 1% levels under $\mathbf{W_1}$ and $\mathbf{W_3}$, respectively. This indicates that clean energy investment has a stronger emissions abatement effect in high-income countries than in middle-income countries.[8] At least three phenomena may contribute to this finding. First, faced with a tradeoff between economic development and environmental protection, less developed economies may be more inclined to favor the former, limiting the scope for emissions reduction initiatives that may come at the cost of economic development. High-income countries, by contrast, may place a greater emphasis on controlling carbon emissions and may institute more supportive policies to encourage the introduction of clean energy technologies. Second, high-income countries typically experience higher rates of productivity and private market activity subject to market discipline than middle-income economies. Both of these forces will tend to reduce the cost of adopting new clean energy technologies (Du et al., 2019). Finally, high-income countries will often have a greater ability to fund ambitious clean energy projects and to meet the potentially large initial and/or ongoing costs associated with exploiting knowledge spillovers.

Interestingly, we find that the indirect effect of $logcei \times H$ is statistically insignificant under all three weighting schemes. This indicates that the indirect effects of clean energy investment on emissions are similar irrespective of whether neighboring countries are in the high-income or middle-income group.

[8]The estimate for the direct effect of $logcei \times H$ under $\mathbf{W_2}$ is smaller than under the other weighting schemes and is statistically insignificant. We conjecture that this finding reflects the construction of $\mathbf{W_2}$, which already accounts for GDP per capita. Therefore, the elements of the weights matrix $\mathbf{W_2}$ will be correlated with the income group dummy, which may reduce the significance of the interaction terms.

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 73 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. This effect is stronger among high-income countries than middle-income countries. 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. Finally, by subsidising clean energy initiatives in middle-income countries, it may be possible to promote convergence onto the level of effectiveness of clean energy investments observed in the high-income group.

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.
$logCO_2$	1387	1.565	0.828	-1.670	3.245
logcei	1387	8.038	2.181	-1.050	13.452
loggdp	1387	9.380	1.193	6.640	11.626
$loggdp^2$	1387	89.415	22.172	44.091	135.163
logpop	1387	16.683	1.587	12.547	21.055
logtrade	1387	4.356	0.530	2.986	6.081
logec	1387	4.375	0.266	2.801	4.681
logdc	1387	17.309	1.656	13.622	21.898

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

	$logCO_2$			*logcei*		
Year	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
2000	0.251***	0.239***	0.281***	0.191***	0.144***	0.228***
2001	0.259***	0.248***	0.292***	0.191***	0.144***	0.228***
2002	0.264***	0.253***	0.288***	0.184***	0.142***	0.223***
2003	0.258***	0.252***	0.289***	0.187***	0.144***	0.227***
2004	0.250***	0.244***	0.276***	0.191***	0.147***	0.232***
2005	0.239***	0.233***	0.276***	0.191***	0.148***	0.232***
2006	0.233***	0.235***	0.274***	0.189***	0.145***	0.230***
2007	0.214***	0.219***	0.255***	0.188***	0.145***	0.230***
2008	0.206***	0.214***	0.237***	0.187***	0.145***	0.230***
2009	0.198***	0.198***	0.223***	0.177***	0.140***	0.225***
2010	0.201***	0.201***	0.226***	0.176***	0.142***	0.216***
2011	0.173***	0.180***	0.193***	0.160***	0.135***	0.206***
2012	0.156***	0.156***	0.175***	0.165***	0.142***	0.200***
2013	0.151***	0.146***	0.176***	0.156***	0.139***	0.194***
2014	0.141***	0.126**	0.159***	0.152***	0.139***	0.195***
2015	0.144***	0.129**	0.160***	0.135***	0.120**	0.184***
2016	0.146***	0.136***	0.167***	0.128***	0.109**	0.183***
2017	0.153***	0.144***	0.171***	0.131***	0.110**	0.186***
2018	0.153***	0.145***	0.175***	0.127***	0.104**	0.178***
Average	0.206***	0.202***	0.232***	0.176***	0.141***	0.218***

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

	Panel A					
Tests	Statistic		Degrees of freedom		p-value	
LR spatial fixed effects	118.981		73		0.001	
LR time fixed effects	529.040		19		0.000	
	Panel B					
	$\mathbf{W_1}$		$\mathbf{W_2}$		$\mathbf{W_3}$	
Tests	Statistic	p-value	Statistic	p-value	Statistic	p-value
LM spatial lag	508.221	0.000	371.202	0.000	516.181	0.000
LM spatial error	683.759	0.000	614.207	0.000	1023.279	0.000
Robust LM spatial lag	19.152	0.000	7.931	0.005	4.203	0.040
Robust LM spatial error	194.689	0.000	250.936	0.000	511.301	0.000
Wald spatial lag	264.732	0.000	340.067	0.000	435.919	0.000
Wald spatial error	26.246	0.000	24.561	0.000	13.923	0.031
Hausman test	63.615	0.000	216.644	0.000	89.603	0.000

Table 4: SDM estimation results for the full sample

	Model 1	Model 2	Model 3
Variables	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
logcei	-0.057***	-0.053***	-0.061***
	(-6.623)	(-6.274)	(-7.234)
loggdp	1.917***	1.905***	2.224***
	(12.710)	(12.893)	(15.214)
$loggdp^2$	-0.074***	-0.073***	-0.089***
	(-9.061)	(-9.122)	(-11.260)
logpop	-0.020	-0.021	-0.010
	(-1.255)	(-1.373)	(-0.636)
logtrade	-0.156***	-0.133***	-0.115***
	(-4.850)	(-4.227)	(-3.660)
logec	0.820***	0.788***	0.794***
	(11.990)	(11.331)	(12.137)
$W * logcei$	0.079***	0.084***	0.063***
	(4.683)	(6.122)	(5.485)
$W * loggdp$	-1.365***	-1.435***	-1.776***
	(-4.487)	(-5.374)	(-8.312)
$W * loggdp^2$	0.051***	0.054***	0.074***
	(3.145)	(3.743)	(6.477)
$W * logpop$	0.043	0.027	0.020
	(1.516)	(1.024)	(0.972)
$W * logtrade$	0.271***	0.222***	0.132***
	(4.691)	(3.783)	(3.056)
$W * logec$	-0.669***	-0.522***	-0.511***
	(-5.392)	(-4.530)	(-5.750)
ρ	0.838***	0.808***	0.697***
	(56.945)	(56.409)	(36.688)
Obs.	1387	1387	1387
Log-likelihood	-320.565	-380.373	-287.184
R^2	0.885	0.875	0.885

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

Table 5: Direct and indirect effects

	Model 1	Model 2	Model 3
Variables	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
Panel A: Direct Effect			
logcei	-0.049***	-0.045***	-0.056***
	(-5.901)	(-5.374)	(-6.803)
loggdp	1.970***	1.919***	2.172***
	(13.587)	(13.246)	(15.256)
$loggdp^2$	-0.077***	-0.074***	-0.087***
	(-9.752)	(-9.405)	(-11.219)
logpop	-0.013	-0.019	-0.007
	(-0.885)	(-1.293)	(-0.472)
logtrade	-0.122***	-0.112***	-0.105***
	(-3.920)	(-3.644)	(-3.404)
logec	0.821***	0.806***	0.800***
	(12.715)	(12.079)	(12.532)
Panel B: Indirect Effect			
logcei	0.188**	0.205***	0.063**
	(2.277)	(3.502)	(2.188)
loggdp	1.475	0.546	-0.694
	(0.967)	(0.467)	(-1.250)
$loggdp^2$	-0.067	-0.026	0.037
	(-0.821)	(-0.416)	(1.248)
logpop	0.165	0.054	0.042
	(1.214)	(0.491)	(0.845)
logtrade	0.848***	0.586**	0.164
	(3.049)	(2.327)	(1.512)
logec	0.107	0.581	0.131
	(0.184)	(1.254)	(0.604)

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

Table 6: Estimated direct and indirect effects from equation (7)

	Model 1	Model 2	Model 3
Variables	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
Panel A: Direct Effect			
logcei	-0.073***	-0.070***	-0.080***
	(-8.478)	(-8.050)	(-9.321)
loggdp	1.837***	1.768***	1.982***
	(12.291)	(11.863)	(13.388)
$loggdp^2$	-0.066***	-0.062***	-0.073***
	(-8.141)	(-7.700)	(-9.059)
logpop	1.030***	1.024***	1.035***
	(66.055)	(66.061)	(66.497)
logtrade	0.041	0.059*	0.052
	(1.269)	(1.850)	(1.621)
logec	0.579***	0.577***	0.584***
	(8.634)	(8.380)	(8.776)
Panel B: Indirect Effect			
logcei	0.252***	0.223***	0.085***
	(3.356)	(3.895)	(2.962)
loggdp	2.528*	1.674	-0.062
	(1.827)	(1.463)	(-0.113)
$loggdp^2$	-0.128*	-0.090	0.001
	(-1.731)	(-1.463)	(0.049)
logpop	0.091	0.036	0.038
	(0.731)	(0.335)	(0.761)
logtrade	1.060***	0.780***	0.287***
	(4.223)	(3.174)	(2.688)
logec	0.199	0.408	0.049
	(0.372)	(0.900)	(0.228)

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

	Model 1	Model 2	Model 3
Variables	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
Panel A: Direct Effect			
logcei	-0.020**	-0.022**	-0.023***
	(-2.219)	(-2.354)	(-2.649)
loggdp	1.664***	1.594***	2.061***
	(9.720)	(9.148)	(11.878)
$loggdp^2$	-0.063***	-0.059***	-0.084***
	(-6.843)	(-6.302)	(-9.001)
logpop	-0.011	0.003	-0.025
	(-0.668)	(0.202)	(-1.573)
logtrade	-0.026	-0.008	-0.071**
	(-0.788)	(-0.225)	(-1.993)
logec	0.917***	0.906***	0.844***
	(12.654)	(12.567)	(11.923)
Panel B: Indirect Effect			
logcei	0.205***	0.132*	0.078**
	(2.770)	(1.808)	(2.295)
loggdp	-3.443***	-1.292	-1.503***
	(-8.368)	(-1.045)	(-2.746)
$loggdp^2$	0.186***	0.072	0.082***
	(8.008)	(1.095)	(2.792)
logpop	-0.143	-0.153	0.043
	(-1.377)	(-1.293)	(0.838)
logtrade	-0.081	-0.104	0.316***
	(-0.386)	(-0.401)	(2.802)
logec	1.116**	1.012*	0.435*
	(2.274)	(1.676)	(1.734)

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

Table 8: Heterogeneity by income level

	Variables	Model 1 $\mathbf{W_1}$	Model 2 $\mathbf{W_2}$	Model 3 $\mathbf{W_3}$
Direct Effect	*logcei*	-0.046***	-0.044***	-0.052***
		(-5.344)	(-5.009)	(-5.972)
	$logcei \times H$	-0.012**	-0.006	-0.015***
		(-2.254)	(-1.128)	(-2.909)
Indirect Effect	*logcei*	0.185**	0.196***	0.059**
		(2.225)	(3.524)	(2.070)
	$logcei \times H$	0.009	-0.003	0.016
		(0.196)	(-0.084)	(0.983)

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

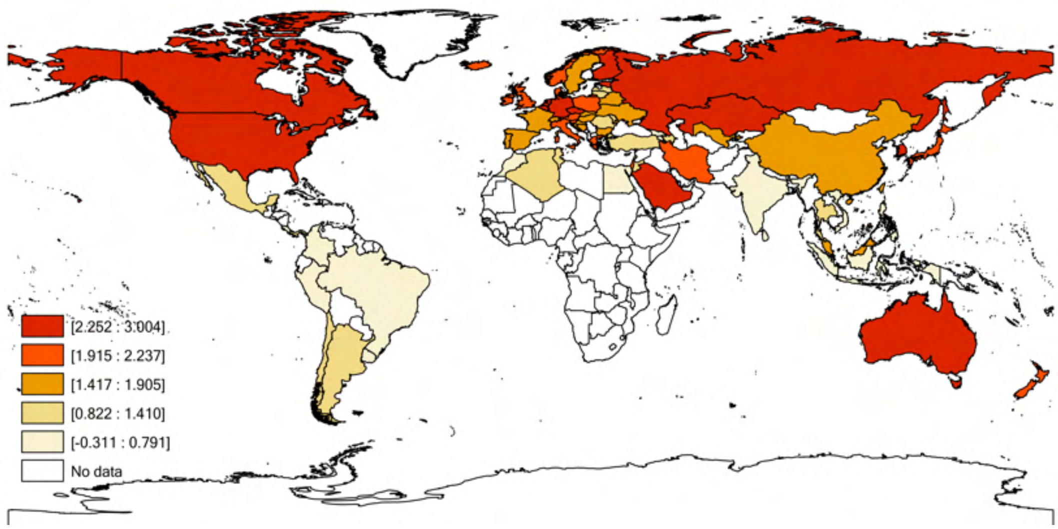
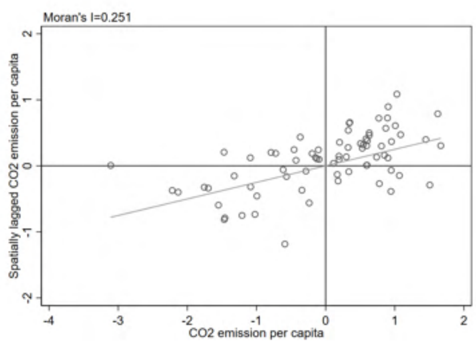
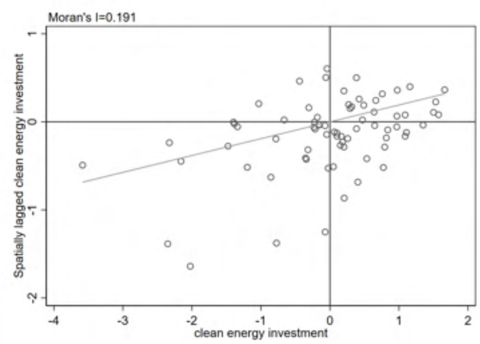


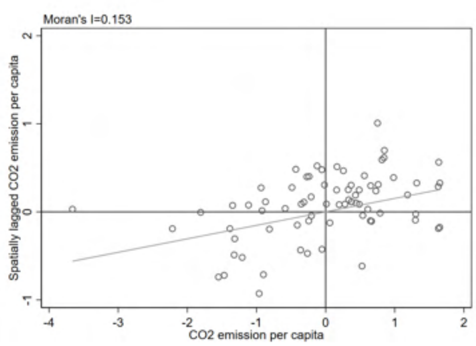
Figure 1: Spatial distribution of the log-arithmetic mean of per capita CO_2 emissions from 2000 to 2018.



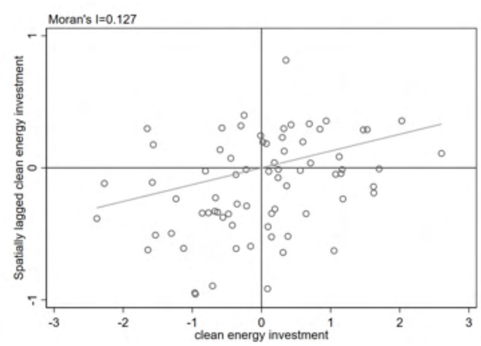
(a) CO_2 emissions, Year=2000



(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	Mid-year estimate of total population	individuals	WDI
Trade openness	Proportion of total exports and imports in GDP	%	WDI
Energy consumption structure	Proportion of fossil fuel consumption in total energy consumption	%	EIA
Dirty energy consumption	Total energy consumption in coal, oil and natural gas	Tonnes of oil equivalent	EIA

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

Table A.2: 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	Saudi Arabia
	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	

Table A.3: Model selection for dirty energy consumption

	Panel A					
Tests	Statistic		Degree of freedom		p-value	
LR spatial fixed test	94.061		73		0.049	
LR time fixed test	447.674		19		0.000	
	Panel B					
	$\mathbf{W_1}$		$\mathbf{W_2}$		$\mathbf{W_3}$	
Tests	Statistic	p-value	Statistic	p-value	Statistic	p-value
LM spatial lag	226.548	0.000	183.251	0.000	213.980	0.000
LM spatial error	704.952	0.000	679.060	0.000	1036.000	0.000
Robust LM spatial lag	17.054	0.000	14.963	0.000	12.864	0.040
Robust LM spatial error	495.458	0.000	510.771	0.000	834.884	0.000
Wald spatial lag	1677.513	0.000	1763.102	0.000	1199.133	0.000
Wald spatial error	37.912	0.000	28.114	0.000	17.757	0.007
Hausman test	64.800	0.000	88.592	0.000	5996.299	0.000

Table A.4: Heterogeneity analysis: estimation results for income dummy

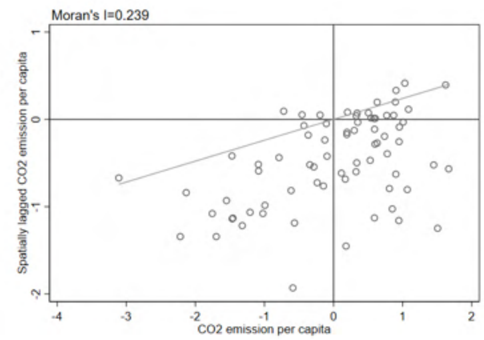
	Model 1	Model 2	Model 3
Variables	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
logcei	-0.053***	-0.051***	-0.055***
	(-5.991)	(-5.888)	(-6.452)
$logcei * H$	-0.012**	-0.006	-0.016***
	(-2.180)	(-1.067)	(-3.024)
loggdp	1.848***	1.870***	2.120***
	(12.016)	(12.333)	(14.163)
$loggdp^2$	-0.069***	-0.071***	-0.082***
	(-8.116)	(-8.401)	(-9.835)
logpop	-0.019	-0.020	-0.010
	(-1.216)	(-1.298)	(-0.654)
logtrade	-0.163***	-0.135***	-0.128***
	(-5.048)	(-4.276)	(-4.044)
logec	0.810***	0.782***	0.776***
	(11.854)	(11.208)	(11.850)
$W * logcei$	0.076***	0.082***	0.058***
	(4.420)	(5.895)	(5.006)
$W * logcei * H$	0.012	0.004	0.017**
	(1.190)	(0.475)	(2.376)
$W * loggdp$	-1.288***	-1.372***	-1.656***
	(-4.194)	(-5.042)	(-7.627)
$W * loggdp^2$	0.046***	0.051**	0.066***
	(2.742)	(3.379)	(5.532)
$W * logpop$	0.041	0.025	0.018
	(1.454)	(0.959)	(0.891)
$W * logtrade$	0.278***	0.225***	0.144***
	(4.803)	(3.809)	(3.327)
$W * logec$	-0.661***	-0.509***	-0.482***
	(-5.252)	(-4.382)	(-5.371)
ρ	0.838***	0.797***	0.696***
	(57.060)	(52.865)	(36.582)
Obs.	1387	1387	1387
Log-likelihood	-318.018	-378.299	-282.268
R^2	0.886	0.874	0.885
Wald spatial lag	261.653***	322.806***	432.572***
Wald spatial error	27.198***	25.170***	14.980**

Notes: Numbers in ( ) are t-statistics. *, **, *** represent the significance at the 10%, 5%, and 1% level, respectively.

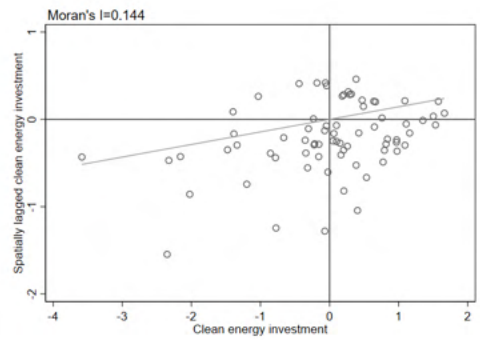
Table A.5: Heterogeneity analysis: Direct and indirect impacts of the models in Table A.4

	Model 1	Model 2	Model 3
Variables	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$
Panel A: Direct Effect			
logcei	-0.046***	-0.044***	-0.052***
	(-5.344)	(-5.009)	(-5.972)
$logcei * H$	-0.012**	-0.006	-0.015***
	(-2.254)	(-1.128)	(-2.909)
loggdp	1.908***	1.891***	2.083***
	(13.035)	(12.862)	(14.421)
$loggdp^2$	-0.072***	-0.071***	-0.080***
	(-8.950)	(-8.868)	(-10.058)
logpop	-0.012	-0.018	-0.007
	(-0.839)	(-1.178)	(-0.462)
logtrade	-0.129***	-0.114***	-0.116***
	(-4.159)	(-3.676)	(-3.713)
logec	0.813***	0.801***	0.786***
	(12.316)	(11.645)	(12.017)
Panel B: Indirect Effect			
logcei	0.185**	0.196***	0.059**
	(2.225)	(3.524)	(2.070)
$logcei * H$	0.009	-0.003	0.016
	(0.196)	(-0.084)	(0.983)
loggdp	1.605	0.594	-0.542
	(1.054)	(0.531)	(-0.965)
$loggdp^2$	-0.074	-0.028	0.027
	(-0.899)	(-0.459)	(0.875)
logpop	0.156	0.047	0.036
	(1.173)	(0.463)	(0.734)
logtrade	0.856***	0.564**	0.174
	(3.084)	(2.378)	(1.618)
logec	0.088	0.530	0.171
	(0.152)	(1.239)	(0.808)

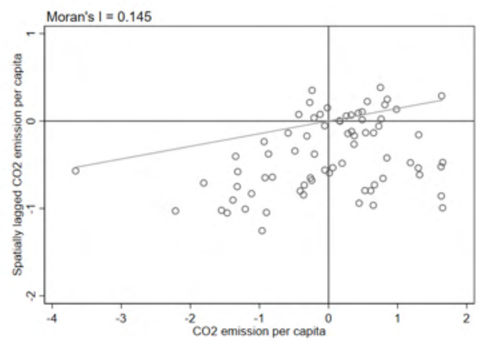
Notes: Numbers in ( ) are t-statistics. *, **, *** represent the significance at the 10%, 5%, and 1% level, respectively.



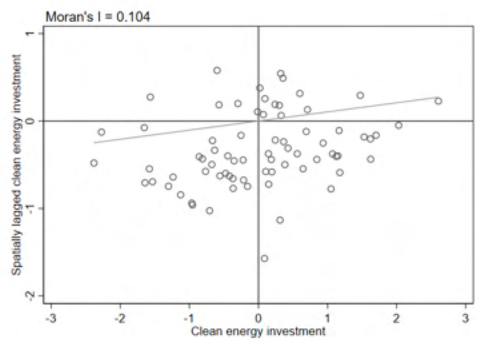
(a) CO_2 emission, Year=2000



(b) Clean energy investment, Year=2000

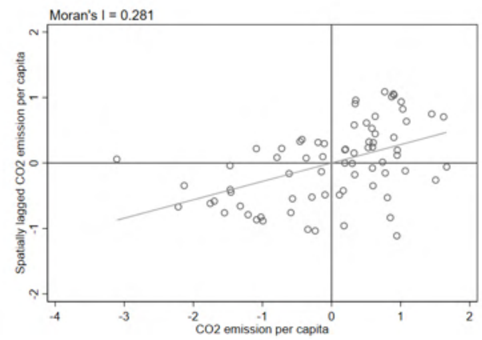


(c) CO_2 emission, Year=2018

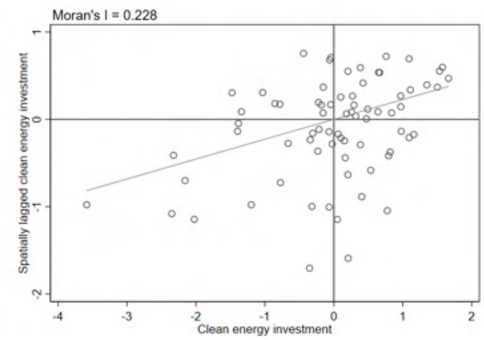


(d) Clean energy investment, Year=2018

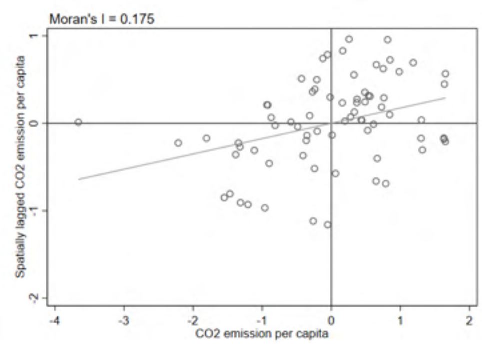
Figure A.1: Moran's I scatter plots of CO_2 emissions and clean energy investment with $\mathbf{W_2}$.



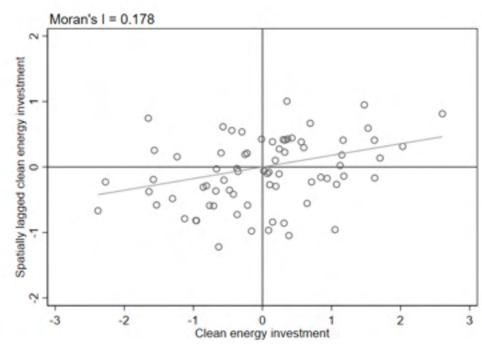
(a) CO_2 emission, Year=2000



(b) Clean energy investment, Year=2000



(c) CO_2 emission, Year=2018



(d) Clean energy investment, Year=2018

Figure A.2: Moran's I scatter plots of CO_2 emissions and clean energy investment with $\mathbf{W_3}$.