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A Time-Varying Analysis of Pollution Spillovers Among EU Countries: Evidence from a TVP-VAR Connectedness Approach

Çağla Bucak [1] & A. Nazif Çatık [1]

[1] Ege University, Faculty of Economics and Administrative Sciences, Department of Economics, İzmir, Türkiye

Abstract

This study explores the spillover effects of carbon emissions among the 16 EU countries from 1980Q1 to 2023Q3, employing the TVP-VAR connectedness methodology. Spillovers are calculated based on the time-varying forecast error variance decompositions of CO_2 emissions for each country. As CO_2 emissions for all countries are integrated of order one, first differences are employed in the analysis. The findings reveal a high level of connectedness among EU countries, with values ranging from 68% to 92% and a Total Connectedness Index of 75.45. Regarding net connectedness, Germany and the UK emerge as the main CO_2 transmitters, with net values of 15.26 and 15.15, respectively, while Greece and Bulgaria are the main receivers, with net values of −30.34 and −14.85. This high connectedness underscores the importance of collaborative efforts among EU countries in developing policies to mitigate environmental degradation. The findings also indicate a positive correlation between economic activity and pollution, with higher-income countries tending to contribute more to pollution spillover. Our results further suggest that EU member states should endeavour to increase the use of renewable energy sources while phasing out nonrenewable ones, in accordance with the overarching objective of environmental protection.

Keywords Spillover · TVP-VAR connectedness · Transmitter · Receiver · CO2 emissions · EU

JEL Classification C01 · Q01 · Q5

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Corresponding author: Çağla Bucak cagla.bucak@ege.edu.tr

A Time-Varying Analysis of Pollution Spillovers Among EU Countries: Evidence from a TVP-VAR Connectedness Approach

Climate change poses a substantial peril to the human race, as it has the capacity to disturb critical aspects of existence, such as food provision, water accessibility, environmental conditions, and the steadiness of marine ecosystems (United Nations, 2021). Climate change also poses a significant threat to sustainable economic growth through its severe environmental degradation. Hence, it is imperative to conduct a thorough examination of the elements that contribute to climate change to identify those that have the potential to disrupt worldwide equilibrium, endanger human life, and cause irreversible damage to the planet (Balsalobre-Lorente et al., 2022).

One of the negative externalities of continuous economic growth is the release of anthropogenic CO_2 emissions, leading to climate change and environmental degradation (Peng et al., 2022). Since the start of the 21st century, there has been a consistent uptrend in global fossil CO_2 emissions compared to the three previous decades, primarily attributable to fossil fuel combustion (Crippa et al., 2022). Achieving sustained economic growth, which is widely recognised as essential, hinges on the continuous provision of essential inputs like energy. However, a significant majority of countries depend heavily on nonrenewable energy sources to meet their increasing energy needs, which has unquestionably worsened environmental challenges (He et al., 2021). The rapid trajectory of global climate change is directly associated with the rising trend of global warming and escalating carbon emissions (Doğan et al., 2021).

There is a growing recent literature analysing environmental pollution spillovers to assess the impact of recent developments in environmental policies to counter climate change. The growing number of studies on spillovers may be due to the connection between economic growth and environmental pollution; consequently, environmental concerns in one country may impact the policy decisions of other countries (You & Lv, 2018). For instance, closely integrated countries may share a similar development trajectory that results in comparable environmental issues. Hence, it is plausible to hypothesise that the spread of environmental issues from one country to another may significantly impact emission reduction programmes in other countries, thereby causing significant environmental degradation concerns (Akram, 2022).

Given this background, the main objective of this study is to investigate air pollution spillovers among EU countries. The EU presents an interesting case to study pollution spillovers. First, as the most important example of economic integration, it is one of the largest contributors to global CO_2 emissions (Crippa et al., 2022). Second, given this status and to pursue environmental solutions, EU countries aim to become the world's first carbon-neutral continent by 2050 as part of the Green Deal. Thus, the EU Commission has proposed increasing the mandatory renewable sources target in the EU's energy mix to 40% and achieving a 36-39% reduction in both final and primary energy consumption by 2030 (European Commission, 2020).

In line with these developments, the energy mix of EU countries has shifted significantly over the past two decades. In 2000, for instance, primary energy consumption by fuel types in the EU stood at 26.79 EJ (exajoules) for oil, 12.92 EJ for natural gas, 11.86 EJ for coal, 8.78 EJ for nuclear energy, 3.79 EJ for hydroelectric power, and 0.65 EJ for renewables. By 2022, the consumption of oil, natural gas, coal, nuclear energy, and hydroelectric power had fallen to 22.13, 12.36, 6.98, 5.48, and 2.60 EJ, respectively, whereas the consumption of renewable energy had increased to 8.63 EJ. The increase in the share of renewable energy sources within the EU's overall energy mix is remarkable, from merely 1% to 14.83% at present. Conversely, there has been a notable decline in the share contributed by the main three fossil fuels, namely, oil, coal, and natural gas, from approximately 79.6% to around 71.28%. Nevertheless, despite ongoing efforts towards reducing carbon emissions and promoting sustainable and environmentally friendly sources of energy, reaching the EU's net zero emission target by 2050 remains a considerable challenge, with EU countries currently ranking among the world's top five emitters (United Nations, 2023).

Against this backdrop, this study aims to contribute to the literature on pollution spillover in two respects. First, while some studies on EU countries have used spatial econometric methodologies, this study is the first to analyse pollution spillovers among EU countries using the novel TVP-VAR connectedness approach. While spatial econometrics techniques offer valuable insights, they have limitations in capturing time-varying relationships among countries. Furthermore, these techniques cannot demonstrate key aspects of CO_2 transmission dynamics, such as contributions to others, contributions from others, and net directional total connectedness. However, the TVP-VAR connectedness approach provides a more precise and detailed comprehension of pollution spillovers. By identifying both the countries that receive and transmit pollution spillovers, it is possible to gain insights into the specific dynamics of pollution transmission within the EU. This method also allows us to evaluate the magnitude of spillover and its variation across countries and over time. Developed by Antonakakis et al. (2020), the TVP-VAR connectedness approach builds upon the Diebold and Yilmaz (2014) methodology that measures forecast error variation in different locations caused by shocks occurring anywhere. However, the Diebold & Yilmaz (2014) method may not effectively capture changes in parameter values, potentially leading to inaccurate results. Additionally, the presence of outliers in the data can distort the estimates in this technique. The subjective choice of an appropriate rolling window size can influence the results and the calculation of connectedness, which may lead to the loss of valuable information. These limitations underscore the need for an enhanced methodology that addresses these issues and improves spillover analysis. Antonakakis et al. (2020) effectively addressed these limitations by refining the methodology and providing a more robust and reliable approach for analysing spillover effects. Second, unlike previous studies, we use the CO_2 emissions of the countries originally available at a quarterly frequency, allowing us to draw more robust statistical inferences. Most prior studies have relied on data with lower frequency or less granularity, limiting their ability to capture the dynamics of pollution transmission effectively. By addressing these gaps in existing research, the findings can assist EU policymakers and stakeholders in developing effective strategies to reduce pollution and promote sustainable development.

The rest of the article is structured as follows. Section 2 reviews previous research analysing pollution spillovers among countries, with a specific emphasis on EU countries. Section three describes the methodology of TVP-VAR connectedness. Section four presents the empirical findings using various connectedness measures. Section five summarises the main findings and discusses some policy implications.

Literature Review

Studies on the Spillover Effects of CO_2 Using Spatial Econometric Methods

The historical framework indicates that environmental problems have been recognised for over five decades, with various conferences and summits being held, and agreements ratified to address the adverse impacts of the climate crisis. The dynamics underlying these environmental problems stem from the negative externalities inherent in environmental issues. These environmental externalities generate costs arising from production, consumption, and resource extraction activities undertaken by responsible agents, while the resulting adverse effects are transmitted to others (Libecap, 2013). Since the atmosphere, nature, and environment constitute global public goods, their excessive use represents a market failure necessitating cooperative policy solutions. When natural resources and environmental boundaries span the geographical territories of two or more sovereign countries, agents in each country can access and exploit the shared resources, which leads to the spillover of environmental problems (Akhundjanov & Muñoz-García, 2019). This issue is particularly pronounced in economically and geographically integrated regions, such as the European Union, where intense trade linkages, shared ecosystems, and regulatory interdependence amplify transboundary environmental effects. The positive spatial spillovers of environmental degradation frequently documented in the empirical literature (e.g., Zhang et al., 2017; Radmehr et al., 2021) can thus be interpreted as manifestations of these uninternalized cross-border costs.

Beyond environmental externalities, the formulation of environmental policies and international agreements can be conceptualised as a process of strategic interaction among countries. Within this framework, policymaking resembles a strategic game in which governments seek to reconcile domestic economic objectives with global environmental commitments (Barrett, 1994). Consequently, a country's emission levels depend not only on domestic conditions but also on the environmental policies and emission trajectories of other countries connected through trade, economic integration, and political relationships. These strategic and economic interdependencies naturally generate cross-country environmental spillover effects.

To combat environmental pollution and climate change and reverse the decline in biodiversity rates, countries have committed to achieving carbon neutrality by 2050, according to their treaty endorsements. Given these developments, any examination of environmental issues within the empirical economics literature requires comprehensive and more complex methodologies. However, conventional econometric methodologies, which do not allow for interdependencies among countries or regions, may fail to account for the analysis of pollution spillover effects.

Considering these factors, several scholars have employed spatial econometric models to analyse pollution spillovers between neighbouring countries. Spatial econometric models are particularly well suited to identifying spillover effects arising from geographical proximity, as they incorporate spatial interactions through a predefined spatial weight matrix. These models typically estimate a single average spillover coefficient of the dependent variable across countries and assume that the underlying spillover structure remains stable over time. For this reason, spatial econometric techniques have been widely used in the economics literature. Researchers including Zhang et al. (2017), You & Lv (2018), Zhang et al. (2018), Li et al. (2019), Abdo et al. (2020), Gu et al. (2020), Li & Li (2020), Murshed et al. (2020), Li & Wang (2022), Pea-Assounga & Wu (2022), Wu et al. (2022), Jeetoo & Chinyanga (2023), Qunfang & Huang (2023), and Tawfeeq (2023) found positive and significant CO_2 emission spillovers between neighbouring countries. Conversely, Al-Silefanee et al. (2022) and Karimi et al. (2022) did not find significant spillover, whereas Wen et al. (2020) and Lin et al. (2022) reported negative spillover effects of CO_2 emissions. Although the majority of studies report positive CO_2 spillover effects, the variation in empirical results indicates that estimated spillovers are highly sensitive to methodological choices, including the type of spatial model employed (SDM, SAR, or SEM), the time period considered, and the selection of country groups. Particularly, differences in the specification of spatial weight matrices can substantially influence both the magnitude and even the direction of spillover effects. Moreover, heterogeneity in the choice and treatment of control variables may further contribute to the inconsistencies observed across studies. Consequently, the mixed evidence in the literature is more likely to reflect methodological limitations and modelling differences rather than the absence of cross-border environmental spillovers.

A few studies have analysed spillover effects of environmental degradation among EU countries using spatial econometric techniques. For instance, Ren et al. (2020) reported a significant positive spatial spillover of CO_2 emissions from 26 adjacent EU countries to the host country. Focusing on 21 EU countries, Radmehr et al. (2021) found that a 1% increase in CO_2 emissions in neighbouring countries leads to a 0.06% rise in CO_2 emissions within the host country. Similarly, for 28 EU countries, Shahnazi & Shabani (2021) found that increasing CO_2 emissions in a country's neighbouring region results in an increase in the country's own CO_2 emissions. In short, these studies demonstrate that environmental degradation spills over across EU countries. Nevertheless, the reliance on annual data and spatial models in these studies limits their ability to capture time-varying CO_2 spillover patterns as well as the evolving roles of transmitter and receiver countries within the EU.

Studies on CO_2 Spillovers Based on the Connectedness Approach

Along with spatial econometric techniques, spillover among the variables has recently been analysed using a spillover index developed by Diebold & Yilmaz (2009). Although spatial econometric approaches provide valuable insights, their ability to capture time-varying interdependencies across countries is limited. Moreover, they do not fully reflect key aspects of CO_2 transmission mechanisms, such as spillovers transmitted to other countries, spillovers received from others, and net directional connectedness. In response to these limitations, the connectedness framework offers a more detailed and dynamic analysis of pollution spillovers by explicitly identifying both transmitting and receiving countries, thereby allowing for a clearer understanding of pollution transmission dynamics and their evolution over time. Diebold and Yilmaz (2009) initially calculated time-varying spillovers using forecast error decompositions obtained from the rolling estimation of VAR models. Diebold and Yilmaz (2012) then extended the DY spillover index by calculating directional spillovers based on generalised forecast error variances independent of the ordering of the variables. Furthermore, Diebold & Yilmaz (2014) introduced a connectedness approach based on forecast error variation in different locations due to shocks occurring anywhere and provided ways for assessing connectedness derived from their prior methodologies. These techniques can be used to measure both the effect of the variables and those of others by distinguishing between net shock transmitters and net shock receivers (Antonakakis et al., 2020). Antonakakis et al. (2020) measured connectedness based on the TVP-VAR model instead of rolling window VAR. In this methodology, there is no requirement to set a window size for estimating the VAR model; rather, connectedness measures are calculated from time-varying decomposition without any loss of observations.

Compared with the other methodologies, relatively few studies have adopted the connectedness approach. The majority of them do not explicitly estimate pollution spillovers; rather, they primarily focus on the connectedness between CO_2 and selected variables. It is also worth mentioning that those studies employed the Diebold & Yilmaz (2012, 2014) approach, where connectedness was calculated from the forecast error decomposition of the linear VAR model. For instance, Mbarek et al. (2014) used CO_2, energy consumption, and GDP in their research. Alola and Bekun (2021) considered CO_2, the West Texas intermediate crude oil price, the World Pandemic Uncertainty Index, and disposable income per capita. Vo and Vo (2022) utilised CO_2, per capita fossil fuel consumption, per capita renewable fuel consumption, per capita real GDP, trade value, and domestic credit provided by the financial sector. Ha (2023) included variables such as CO_2, the number of individuals using the internet, mobile cellular subscriptions, green technology development, renewable energy consumption, and economic complexity in their study. Jebabli et al. (2023) focused on CO_2 and economic growth. Kanas et al. (2023) analysed CO_2, systemic risk, percentage change in bank assets, real GDP growth, and percentage change in insured losses. Pagnottoni (2023) investigated the connectedness between CO_2, cryptocurrencies, and energy prices. Lastly, Zhang et al. (2023) analysed the connectedness between CO_2, the energy demand of bitcoin, bitcoin returns, bitcoin volatility, and hash rate. Each of the aforementioned studies yielded substantial findings regarding both transmitter and receiver components, in addition to identifying notable spillover effects. Although these studies offer valuable policy insights grounded in econometric analysis, they do not focus exclusively on CO_2 spillover effects nor adequately account for their time-varying nature.

In our review of the literature, only two studies, i.e., Akram (2022) and Shirazi & Šimurina (2022), analysing pollution spillovers among the regions or countries, were identified based on the connectedness approach. Akram (2022) employed annual data and analysed spillover and connectedness of agricultural GHG emissions across continents. While the study provides evidence of time-varying connectedness, its focus on broad continental aggregates may lead to overly general policy implications and obscure country-level heterogeneity. Moreover, the use of annual data limits the ability to capture long-term dynamics. Similarly, Shirazi and Šimurina (2022) analysed pollution spillovers using annual CO_2 emissions categorised by sector and source from energy consumption in the USA. However, the exclusive focus on a single country and the reliance on conventional VAR-based connectedness measures restrict the analysis of time-varying spillover dynamics. These limitations highlight the need for studies that examine wider and more integrated country groups, such as the European Union, employ higher-frequency data, and adopt the TVP-VAR connectedness framework proposed by Antonakakis et al. (2020).

Our study seeks to fill the following research gaps in the literature: Firstly, in contrast to studies employing data with annual frequency, our study uses CO_2 emissions originally available at a quarterly frequency. This allows us to capture the time-varying nature of environmental degradation, providing a more accurate assessment of spillovers among countries. Secondly, our study targets EU countries. Focusing on EU countries enables us to derive insights into the effectiveness of international agreements and collaborations, such as the Paris Climate Agreement and the Green New Deal. Our study contributes to the formulation and discussion of necessary policies within the framework of international cooperation. Thirdly, to the best of our knowledge, no studies have investigated CO_2 emission spillovers among EU countries using Antonakakis et al.'s (2020) TVP-VAR connectedness approach, which offers greater robustness and reliability than the methodologies employed in previous studies.

Based on these gaps, the study addresses the following research questions. i) How do CO_2 emission spillovers among EU countries evolve over time when analysed using high-frequency data? ii) Which EU countries act as net transmitters and which act as net receivers of CO_2 emission spillovers?

Methodology and data

Research methodology

This study used the TVP-VAR connectedness approach developed by Antonakakis *et al.* (2020) based on Diebold & Yilmaz's (2014). The structure of the to analyse pollution spillovers among EU countries. In this study, *spillover* refers to the extent to which an unanticipated shock in one country's carbon emissions arising from policy interventions, macroeconomic fluctuations, or technological developments accounts for variations in the forecast error variance of emissions in other member states. Importantly, this concept does not denote the physical cross-border movement of pollutants or atmospheric leakage. Rather, it captures the statistical diffusion of shocks and the degree of connectedness and synchronisation in emission dynamics across the European Union (Akram, 2022; Shirazi & Šimurina, 2022). By employing forecast error variance decomposition, the analysis reveals how disturbances originating in a single national emission trajectory transmit through the EU's integrated economic and regulatory framework. The TVP-VAR model, allowing for the variance-covariance matrix to change over time, is defined by the following three sets of equations:

$$y_t = A_t z_{t-1} + \varepsilon_t \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$(A_t) = (A_{t-1}) + \xi_t \xi_t \mid \Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

with

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ . \\ . \\ . \\ y_{t-p} \end{pmatrix} A_t' = \begin{pmatrix} A_{1t} \\ A_{2t} \\ . \\ . \\ . \\ A_{pt} \end{pmatrix} \tag{3}$$

Here, Ω_{t-1} denotes the available information until t-1. y_t, z_{t-1} and ε_t represents *m* x 1, *mp* x 1 and *m* x 1 vectors, including the current and lagged values of CO_2 emissions, respectively. A_t and A_t' show the *m* x *mp* and *m* x *m* dimensional matrices, respectively. ξ_t is the *m²p* x 1-dimensional vector. Time-varying variance-covariance matrices are denoted by Σ_t and Ξ_t are with *m* x *m* and *m²p* x *m²p* dimensions, respectively. Finally, *vec*(A_t) represents the vectorised form of A_t with a *m²p* x 1 dimension.

In the TVP-VAR connectedness approach, connectedness measures are computed from generalised impulse response functions (GIRF) and generalised forecast error variance decompositions (GFEVD) (Diebold & Yilmaz, 2014). To achieve this, the TVP-VAR model is converted into the vector moving average (VMA) form. The representation, based on the Wold theorem, is given by:

$$y_t = J'(M_t(z_{t-2} + \eta_{t-1}) + n_t) \tag{4}$$

$$= J'(M_t(M_t(z_{t-3} + \eta_{t-2}) + n_{t-1}) + n_t) \tag{5}$$

$$\vdots \tag{6}$$

$$= J'\left(M_t^{k-1} z_{t-k-1} + \sum_{j=0}^{k} M_t^j \eta_{t-j}\right) \tag{7}$$

with

$$M_t = \begin{pmatrix} A_t & . \\ I_{m(p-1)} & 0_{m(p-1)\,x\,m} \end{pmatrix} \quad n_t = \begin{pmatrix} \epsilon_t \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix} = J\epsilon_t \quad J = \begin{pmatrix} I \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix} \tag{8}$$

Here, M_t represents the *mp* x *pm* dimensional matrix whereas J denotes the *mp* x *m* dimensional matrix and n_t stands for the *mp* x 1-dimensional vector.

Taking the limit as k approaches ∞ gives the following:

$$y_t = \lim_{k\to\infty} J'(M_t^{k-1} z_{t-k-1} + \sum_{j=0}^{k} M_t^j \eta_{t-j}) = \sum_{j=0}^{\infty} J' M_t^j \eta_{t-j} \tag{9}$$

$$y_t = \sum_{j=0}^{\infty} J' M_t^j J \epsilon_{t-j} \qquad B_{jt} = J' M_t^j J, \quad j = 0, 1, ... \tag{10}$$

$$y_t = \sum_{j=0}^{\infty} B_{jt} \epsilon_{t-j} \tag{11}$$

Here B_{jt} indicates an m x m dimensional matrix.

The GIRFs $(\psi_{ij,t}(H))$ show the responses of all variables *j* following a shock in variable *i*. Here, the differences between an H-step-ahead forecast are calculated with and without variable *i* being shocked. This can be computed in the following manner:

$$GIRF_t(H, \delta_{j,t}, \Omega_{t-1}) = E(y_{t+H} \mid e_j = \delta_{j,t}, \Omega_{t-1}) - E(y_{t+J} \mid \Omega_{t-1}) \tag{12}$$

$$\psi_{j,t}(H) = \frac{B_{H,t}\sum_t e_j}{\sqrt{\sum_{jj,t}}}\frac{\delta_{j,t}}{\sqrt{\sum_{jj,t}}} \qquad \delta_{j,t} = \sqrt{\sum_{jj,t}} \tag{13}$$

$$\psi_{j,t}(H) = \sum_{jj,t}^{-\frac{1}{2}} B_{H,t}\sum_t e_j \tag{14}$$

Here, e_j is an *m* x 1 selection vector with unity in the *th* rank and 0 otherwise. GFEVD($\tilde{\phi}_{ij,t}(H)$) is pairwise directional connectedness from *j* to *i*. It represents the effect variable *j* has on variable *i*. It is measured as:

$$\tilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1}\psi_{ij,t}^2}{\sum_{j=1}^{m}\sum_{t=1}^{H-1}\psi_{ij,t}^2} \tag{15}$$

where $\sum_{j=1}^{m}\tilde{\phi}_{ij,t}(H)$ = 1 and $\sum_{i,j=1}^{m}\tilde{\phi}_{ij,t}(H)$ = *m*. In Eq. 15, the denominator indicates the cumulative impact of all shocks, whereas the numerator shows the cumulative impact of a shock of in variable *i*.

Using Eq. 15, the total connectedness index is constructed as follows:

$$C_t(H) = \frac{\sum_{i,\,j=1,\ i\neq j}^{m}\tilde{\varnothing}_{ij,t}(H)}{\sum_{i,\,j=1}^{m}\tilde{\varnothing}_{ij,t}(H)} * 100 = \frac{\sum_{i,\,j=1,\ i\neq j}^{m}\tilde{\varnothing}_{ij,t}(H)}{m} * 100. \tag{16}$$

This connectedness index shows how a shock that occurred in one variable spills over to other variables. If variable *i* transmits its shock to all other variables *j*, it is labelled “total directional connectedness to others” and calculated as follows:

$$C_{i\to j,t}(H) = \frac{\sum_{j=1,\ i\neq j}^{m}\tilde{\varnothing}_{ij,t}(H)}{\sum_{j=1}^{m}\tilde{\varnothing}_{ij,t}(H)} * 100. \tag{17}$$

When variable *i* receives shocks from all variables *j*, it is labelled “total directional connectedness from others” and calculated as follows:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,\ i\neq j}^{m}\tilde{\varnothing}_{ij,t}(H)}{\sum_{i=1}^{m}\tilde{\varnothing}_{ij,t}(H)} * 100. \tag{18}$$

“Net total directional connectedness,” which is the difference between total directional connectedness to others and total directional connectedness from others, illustrates the impact of variable *i* on the network. It is written as follows:

$$C_{i,t} = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \tag{19}$$

If $C_{i,t}$ is positive, variable *i* affects the network more than being affected itself. Conversely, if it is negative, variable *i* is influenced by the network. Lastly, net total directional connectedness can be broken down to measure bidirectional relationships by calculating “net pairwise directional connectedness.”

$$NPDC_{ij}(H) = \tilde{\varnothing}_{jit}(H) - \tilde{\varnothing}_{jit}(H))*100. \tag{20}$$

If $NPDC_{ij}(H)$ is higher than zero, it indicates that variable *i* dominates variable *j*. When it is lower than zero, it indicates that variable *j* dominates variable *i*.

Although the TVP-VAR connectedness approach provides a robust framework for capturing time-varying spillovers, the statistical relationships in CO_2 emissions are fundamentally driven by underlying economic interdependencies. This study is based on the premise that pollution spillovers within the EU reflect real economic and policy mechanisms, transmitted through economic activities and crises, such as the 2008 financial crisis or the COVID-19 pandemic. Given the high level of economic integration and trade within the EU, region-wide expansions or recessions simultaneously affect aggregate demand. Most environmental economists agree that GDP and CO_2 emissions tend to move together over the business cycle (Doda, 2014; Cohen *et al.*, 2022). This synchronised economic activity generates concurrent fluctuations in emissions, meaning that changes in economic activity can directly influence the magnitude and direction of pollution spillovers.

Dataset

This study aimed to estimate the dynamic connectedness and spillover of CO_2 emissions among 16 EU countries. To do so, quarterly CO_2 emissions data from 1980Q1 to 2023Q3 were derived from the Refinitiv Eikon Datastream (2023) database. The countries and the period were selected based on data availability. The 16 sampled EU countries were Austria, Belgium, Bulgaria, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Romania, Spain, Sweden, and the United Kingdom.[1] CO_2 emissions were converted to their natural logarithm before the analysis.

Descriptive statistics for the CO_2 emissions are presented in Figure 1 and Table 1. Figure 1 shows that CO_2 emissions have decreased synchronously in 16 countries. Germany is the largest CO_2 emitter, followed by the United Kingdom, Italy, and France. Notably, the COVID-19 outbreak resulted in a significant decrease in emissions in 2020, which can be attributed to various restrictive measures, such as stay-at-home directives, lockdown protocols, travel limitations, border closures impacting trade, and a subsequent decrease in production. However, the EU's CO_2 emissions surged after the COVID-19 pandemic ended due to a return to pre-pandemic conditions.

Figure 1

Emissions in 16 EU Countries

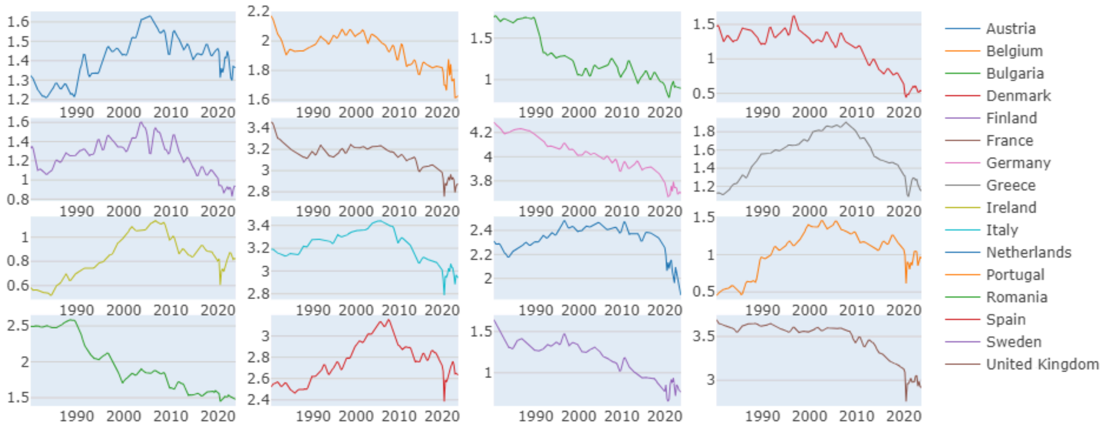


Table 1

Descriptive Statistics

	Mean	Variance	Skewness	Ex. Kurtosis	JB	Q(10)	$Q^2(10)$
Austria	1.412	0.013	-0.044	-0.861***	5.459*	799.179***	799.014***
Belgium	1.94	0.012	-0.734***	0.326	16.478***	618.318***	626.894***
Bulgaria	1.268	0.081	0.623***	-0.936***	17.705***	832.223***	842.606***
Denmark	1.162	0.082	-0.975***	-0.169	27.909***	785.338***	767.767***

[1]Although the United Kingdom formally left the European Union in 2020, it is included in the sample for two reasons. First, the UK was an EU member state for the majority of the sample period (1980–2020), during which its emissions were an integral part of the EU's environmental and regulatory framework. Second, due to strong economic, trade, and geographical linkages, UK carbon emissions have continued to exert spillover effects on EU countries even after 2020. Therefore, for analytical consistency and to capture long-term and persistent cross-border spillovers, the UK is retained in the sample.

	Mean	Variance	Skewness	Ex. Kurtosis	JB	Q(10)	$Q^2(10)$
Finland	1.25	0.030	−0.301*	−0.484	4.353	702.062***	686.967***
France	3.144	0.013	−0.666***	1.293***	25.128***	630.293***	627.832***
Germany	4.021	0.023	−0.321*	−0.505	4.858*	800.519***	803.958***
Greece	1.544	0.056	−0.287	−1.045***	10.366***	819.930***	839.063***
Ireland	0.84	0.031	−0.097	−0.944***	6.774**	865.287***	870.284***
Italy	3.224	0.018	−0.445**	−0.259	6.255**	798.034***	807.339***
Netherlands	2.332	0.013	−1.620***	3.018***	142.935***	615.479***	635.284***
Portugal	1.048	0.082	−0.682***	−0.698***	17.130***	818.652***	830.337***
Romania	1.958	0.137	0.439**	−1.230***	16.642***	875.589***	878.979***
Spain	2.767	0.037	0.23	−0.885***	7.248**	839.118***	843.590***
Sweden	1.19	0.047	−0.540***	−0.594**	11.062***	769.782***	753.306***
UK	3.475	0.042	−1.474***	1.108**	72.318***	777.582***	787.142***

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. JB stands for the Jarque & Bera (1980) normality test. Skewness and kurtosis were calculated using the methods of D'Agostino (1970) and the Anscombe and Glynn (1983) statistics. Q(10) and Q2(10) represent the weighted Ljung-Box statistic for assessing serial correlation in CO_2 emissions and its squared value, as proposed by Fisher & Gallagher (2012).

Table 2
Unit Root Tests

Level	**ADF**		**PP**	
Variables	Intercept	Trend and intercept	Intercept	Trend and intercept
Austria	−1.5499	−0.5303	−1.4443	−1.2265
Belgium	0.8597	−0.9348	−1.1173	−2.1068
Bulgaria	−1.1026	−1.9047	−1.2169	−2.0842
Denmark	0.0144	−1.6159	−0.0997	−1.5721
Finland	−1.1077	−1.4116	−1.269	−1.5291
France	−0.9865	−2.4001	−1.7018	−2.3861
Germany	0.0621	−3.0539	0.0202	−2.4771
Greece	−1.4559	−0.4062	−0.9935	−0.1061
Ireland	−1.4956	−0.7192	−1.5139	−0.725
Italy	−0.2246	−0.807	−0.0859	−0.5593
Netherlands	−1.1373	0.6242	1.2869	3.4565
Portugal	−2.0617	−1.1956	−2.0585	−0.957
Romania	−0.9523	−2.4498	−0.8468	−2.1475
Spain	−1.3888	−0.7252	−1.4254	−0.7252
Sweden	0.7234	−1.7602	−1.0426	−2.5889
UK	1.0666	−0.724	1.4006	−0.741
First-difference	**ADF**		**PP**	
	Intercept	Trend and intercept	Intercept	Trend and intercept
ΔAustria	−5.8448***	−8.7891***	−8.4339***	−8.458***
ΔBelgium	−2.9789**	−3.3433*	−12.6952**	−13.2774*
ΔBulgaria	−5.8225***	−5.82***	−4.6272***	−4.5784***
ΔDenmark	−8.891***	−6.7973***	−4.3146***	−4.2862***

Level	ADF		PP	
ΔFinland	-8.3968***	-4.8409***	-4.9515***	-4.8314***
ΔFrance	-8.569***	-8.5431***	-13.9414***	-13.898***
ΔGermany	-4.382***	-4.4314***	-11.4911***	-11.6035***
ΔGreece	-1.8133	-3.6355**	-5.715	-4.5587**
ΔIreland	-13.6888***	-13.8797***	-13.6951***	-13.8596***
ΔItaly	-13.866***	-6.5483***	-13.8608***	-14.379***
ΔNetherlands	-1.6934	-3.2865*	-12.2917	-12.6534*
ΔPortugal	-14.468***	-14.7551***	-14.4436***	-14.9856***
ΔRomania	-6.3156***	-6.3011***	-6.417***	-6.4001***
ΔSpain	-13.2618***	-13.3903***	-13.2618***	-13.3903***
ΔSweden	-5.2247***	-5.444***	-11.166***	-11.1159***
ΔUK	-16.8056***	-17.0111***	-17.6516***	-21.0604***

Note: The lag length for the ADF test was selected based on the Schwarz information criterion (SIC). The PP test was estimated on the basis of the Bartlett-Kernel test using the Newey-West bandwidth. The null hypothesis is that the series are nonstationary. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The descriptive statistics in Table 1 reveal that CO_2 emissions vary significantly among the 16 countries. For example, Belgium has the lowest variance, whereas Romania has the highest. Regarding mean values, Germany, the UK, Italy, and France have the highest mean CO_2 emissions levels, whereas Denmark, Portugal, and Ireland have the lowest. The CO_2 emissions of Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Portugal, Sweden, and the UK are significantly negatively skewed, whereas those of Bulgaria and Romania are significantly positively skewed. Austria, Bulgaria, Greece, Ireland, Portugal, Romania, Spain, and Sweden have platykurtic distributions, whereas France, the Netherlands, and the UK have notably leptokurtic distributions. Based on the Jarque-Bera test, only Finland's emissions data follow a normal distribution. The results of the Q(10) and $Q^2(10)$ tests indicate autocorrelation among emissions, whereas the unit root test results shown in Table 2 indicate that all the series exhibit stationarity at their first difference. Therefore, all the series are integrated of order one (I(1)). The evidence of the non-stationarity of all variables suggests that CO_2 emissions should be included in their first difference form in the TVP-VAR estimation.

Empirical Findings

After defining the time series properties of the CO_2 emissions, the TVP-VAR model defined by equations (1), (2), and (3) was estimated, and the connectedness measures defined in the methodology section were calculated to analyse pollution spillovers among the 16 EU countries. Time-varying connectedness measures were computed based on generalised forecast error variance decompositions. The TVP-VAR is estimated using the Bayesian framework using Minnesota prior.[2]

Figure 2 presents the results from the dynamic total connectedness measure defined by Eq. (16). As is evident from the black-shaded area, the countries are interconnected, with the extent of connectedness ranging between 68% and 92%. Hence, it can be inferred that pollution spillover among these EU countries is substantial and varies considerably over time. The methodology follows the TVP-VAR connectedness approach developed by Antonakakis et al. (2020). Specifically, spillover is not used as the physical trans-

[2]As quarterly data are employed in this study, the forecast horizon was set to 12. Based on the Akaike Information Criterion, the optimal lag length was selected as 4. The analysis was conducted using the ConnectednessApproach package in R. The forgetting factors governing the time variation in the state and observation equations were set to $\kappa_1 = 0.99$ and $\kappa_2 = 0.96$, respectively, while the hyperparameter γ was fixed at 0.1, in line with the existing literature.

boundary movement of pollution but as the transmission of shocks and information flow among the system's variables.

The connectedness fell in 2009 due to the financial crisis, which led to bankruptcies and reduced production. This in turn reduced CO_2 emissions because higher production levels are typically associated with increased pollution. This finding is supported by Peters et al. (2012), who concluded that the global financial crisis only affected emissions for a short time due to the decline in production-based emissions and a significant decrease in international trade, stemming from the declining trend of consumption-based emissions. In particular, Declercq et al. (2011) highlighted that the economic downturn in 2008 led to a substantial decrease in economic activity. Industrial activity, as well as electricity and fuel demand, fell significantly. Conversely, emissions rose as countries emerged from the crisis due to increasing trade, production, and growth levels, and consequently greater connectedness. Connectedness also decreased in 2020 due to the COVID-19 outbreak, leading to a fall in CO_2 emissions, whereas it increased after COVID-19 restrictions were lifted. In alignment with our findings, Quéré et al. (2021) argued that the temporary measures adopted by countries have only a minimal influence on the prevailing fuel-based structure across all countries. Consequently, the fundamental causes behind emissions resurfaced. Similarly, Nguyen et al. (2021) argued that substantial falls in output, transportation, and energy demand due to the limited movement of individuals during the pandemic led to significant drops in emissions of greenhouse gases, such as CO_2. These arguments are also valid for EU countries (Jawadi et al., 2023). Figure 2 shows that connectedness after the COVID-19 outbreak seems to have become stronger, with countries' emissions spilling over and affecting themselves.

Figure 2

Total Dynamic Connectedness across 16 EU Countries

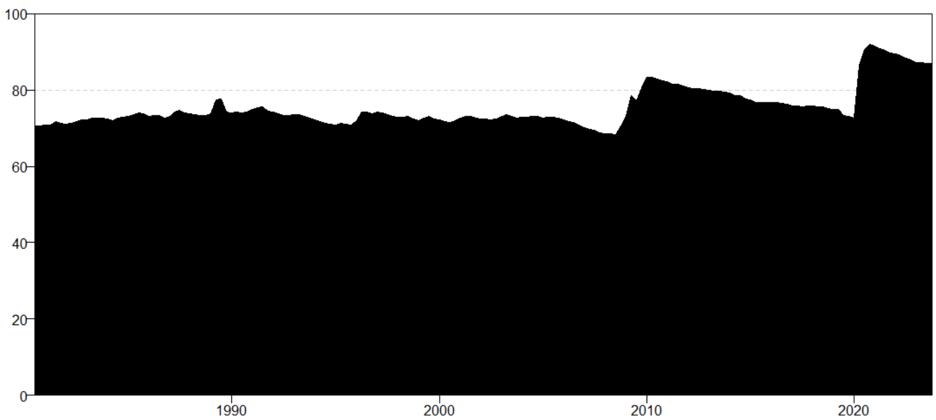


Table 3 summarises the connectedness of each country to identify the emissions transmitters and receivers among the 16 EU countries. The TCI value is 75.45, indicating a strong connectedness relationship between these countries. Particularly notable co-movements are observed between Belgium and Germany, Bulgaria and Romania, Denmark and Finland, Ireland and the UK, Italy and, and Spain, and Portugal and Spain. Interestingly, these co-movements may have occurred because these countries are also close geographically. Regarding their contributions to others, the UK, Germany, Italy, and France exhibit the highest spillover effects on other countries, with values of 96.64, 95.02, 93.26, and 91.39, respectively. Conversely, the UK and France are significantly influenced by other countries, with values of 81.49 and 80.93, respectively. In terms of net connectedness measures, Germany and the UK emerge as the main CO_2 transmitters within the network, with net values of 15.26 and 15.15, respectively. Conversely, Greece and Bulgaria are the main receivers, with net values of −30.34 and −14.85, respectively. Finally, Austria, Belgium, France, Ireland, Italy, Portugal, and Spain are identified as transmitter countries within this network, whereas Denmark, Finland, the Netherlands, Romania, and Sweden are identified as receiver countries.

Although this study primarily focuses on examining CO_2 spillovers among EU countries, the results reveal an intriguing pattern: countries with higher GDP per capita tend to act as net transmitters, whereas lower-income countries generally serve as net receivers. This observation suggests that income levels may influence the magnitude of spillover effects, a notion supported by Doda (2014) and Cohen et al. (2022), who found that CO_2 emissions and GDP exhibit synchronised movements over the business cycle.[3]

Table 3

Dynamic Connectedness Results

	Austria	Belgium	Bulgaria	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Romania	Spain	Sweden	UK	From
Austria	22.53	5.91	3.00	6.83	5.17	6.67	8.86	1.61	5.21	6.59	6.06	3.74	3.17	3.52	4.59	6.55	77.47
Belgium	7.11	21.86	1.92	3.43	4.05	10.14	11.70	2.25	5.14	5.37	7.33	2.32	1.50	2.20	6.75	6.93	78.14
Bulgaria	4.29	2.61	32.42	3.06	2.82	3.43	4.20	5.02	2.83	5.81	2.08	3.90	17.37	4.24	2.75	3.17	67.58
Denmark	6.41	4.24	2.37	27.20	17.81	4.08	6.29	1.51	2.18	2.09	4.49	5.63	1.74	3.56	6.44	3.97	72.80
Finland	6.05	5.85	2.24	16.13	28.60	2.75	7.00	2.47	3.29	2.92	3.78	5.14	1.91	2.16	5.85	3.86	71.40
France	7.06	8.87	1.56	3.12	2.02	19.07	6.63	1.75	6.19	9.12	7.97	5.28	1.52	6.07	4.31	9.47	80.93
Germany	8.10	9.81	2.79	6.10	5.46	6.28	20.24	2.44	3.81	4.57	7.26	3.57	3.88	3.14	6.28	6.27	79.76
Greece	2.70	3.59	6.16	2.23	3.40	3.83	3.81	28.10	7.08	7.66	2.53	6.14	5.51	8.64	3.42	5.20	71.90
Ireland	6.17	4.75	1.57	1.80	2.65	7.05	5.08	4.09	21.35	7.64	5.18	5.76	1.95	8.54	3.98	12.43	78.65
Italy	6.31	4.28	3.69	1.25	2.21	8.50	4.64	3.72	7.12	20.94	4.78	7.64	3.27	11.05	2.82	7.78	79.06
Netherlands	7.29	8.01	1.44	4.88	3.27	8.55	9.07	1.87	5.37	6.12	21.35	2.24	1.77	3.46	6.51	8.79	78.65
Portugal	2.78	2.77	1.96	4.83	5.76	6.95	3.06	2.74	6.27	8.99	2.25	27.36	2.06	15.75	1.30	5.16	72.64
Romania	3.76	2.60	17.80	2.19	2.52	3.08	5.60	4.01	3.11	4.72	2.41	3.45	35.06	3.54	2.33	3.82	64.94
Spain	3.90	2.14	2.52	5.49	4.75	6.40	3.28	3.81	7.73	10.72	3.26	13.32	2.15	20.87	2.77	6.88	79.13
Sweden	6.34	8.15	2.00	8.04	5.75	4.98	8.55	1.90	4.56	3.37	7.11	1.58	1.95	2.07	27.30	6.35	72.70
UK	6.54	5.91	1.70	3.00	2.21	8.69	7.24	2.35	10.75	7.58	7.42	4.27	2.55	6.22	5.05	18.51	81.49
To	84.82	79.49	52.73	72.37	69.85	91.39	95.02	41.56	80.64	93.26	73.90	73.99	52.31	84.15	65.15	96.64	1207.2
Net	7.35	1.35	−14.85	−0.43	−1.55	10.46	15.26	−30.34	1.99	14.20	−4.75	1.35	−12.63	5.02	−7.55	15.15	TCI:75.45

Note: TCI stands for Total Connectedness Index. A positive net value indicates that a country is a net transmitter of carbon emissions, whereas a negative net value indicates that it is a net receiver.

[3] We obtained GDP per capita (constant 2010 US$) data from Refinitiv Eikon DataStream (2023), with the latest data applying to 2022. According to the 2022 data, Greece and Bulgaria have income values of 20,167 and 9,502, respectively. In contrast, the UK's and Germany's income values are 47,232 and 43,032, respectively.

Figure 3

CO_2 Contributions to Others

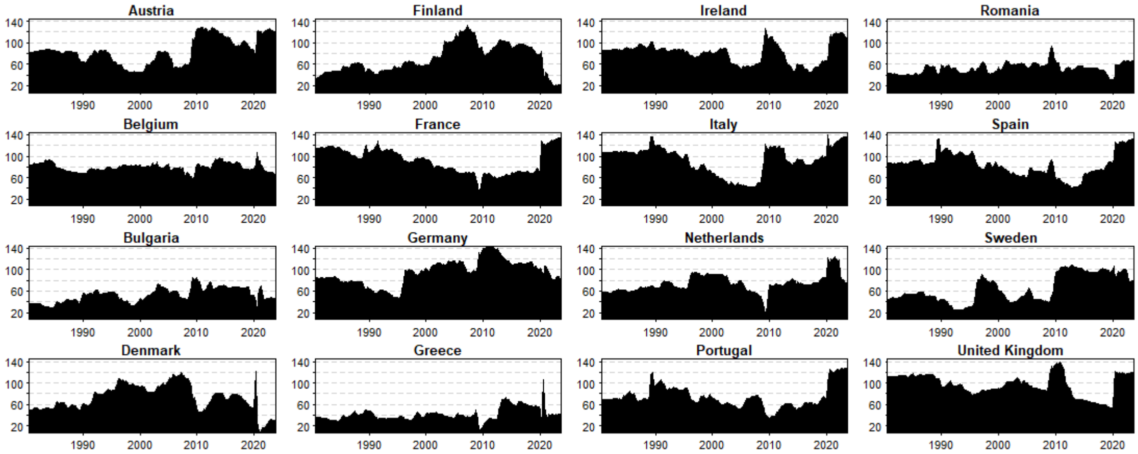


Figure 4

CO_2 Contributions from Others

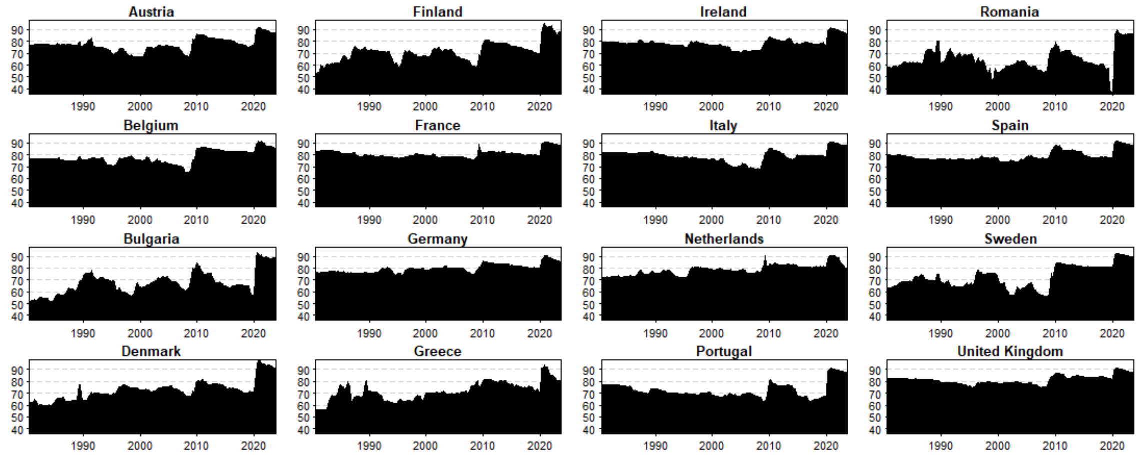
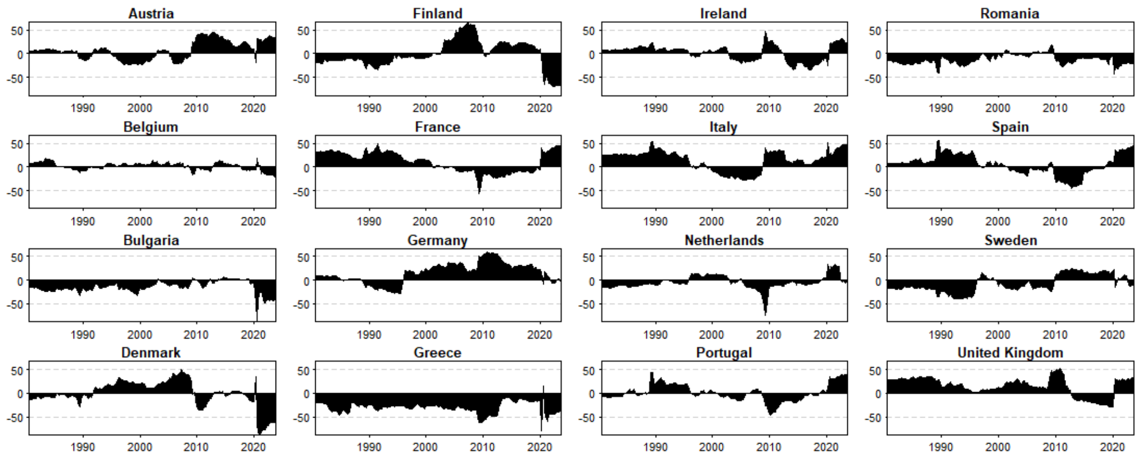


Figure 5

Net Directional Total Connectedness across 16 EU Countries



Figures 3, 4, and 5 show how connectedness measures varied over the analysis period. The results show that pollution spillovers were time-varying in that all 16 countries have been both transmitters and receivers at some point. That is, carbon emissions within the EU certainly spill over, affecting each country's own emissions and environmental policies. These spillover findings are similar to those of Akram (2022) and Shirazi & Šimurina (2022), who applied the DY methodology. For EU countries, the existence of spillover is supported by the findings of Ren et al. (2020), Radmehr et al. (2021), and Shahnazi & Shabani (2021), who used spatial econometric models. The presence of spillover and connectedness indicates that EU countries must collaborate when designing policies aimed at mitigating environmental degradation. These policy implications will be discussed in the conclusion section.

Robustness Check

In this section, we conduct a comprehensive set of robustness checks. The connectedness measures may be affected by the number of lags used in the TVP-VAR model. To account for this, the number of lags in the model is set to three based on the Schwarz Information Criterion. The corresponding net connectedness results are presented in Figure 6. As shown in the figure, the findings are highly consistent with those reported in Figure 5. As an additional robustness check, the forecast horizon is revised to $h = 8$, and the resulting estimates are illustrated in Figure 7. A comparison of Figures 6 and 7 confirms that the main empirical results remain qualitatively unchanged, indicating that the connectedness findings are robust to alternative TVP-VAR specifications.

Figure 6

Net Directional Total Connectedness across 16 EU Countries (lag = 3).

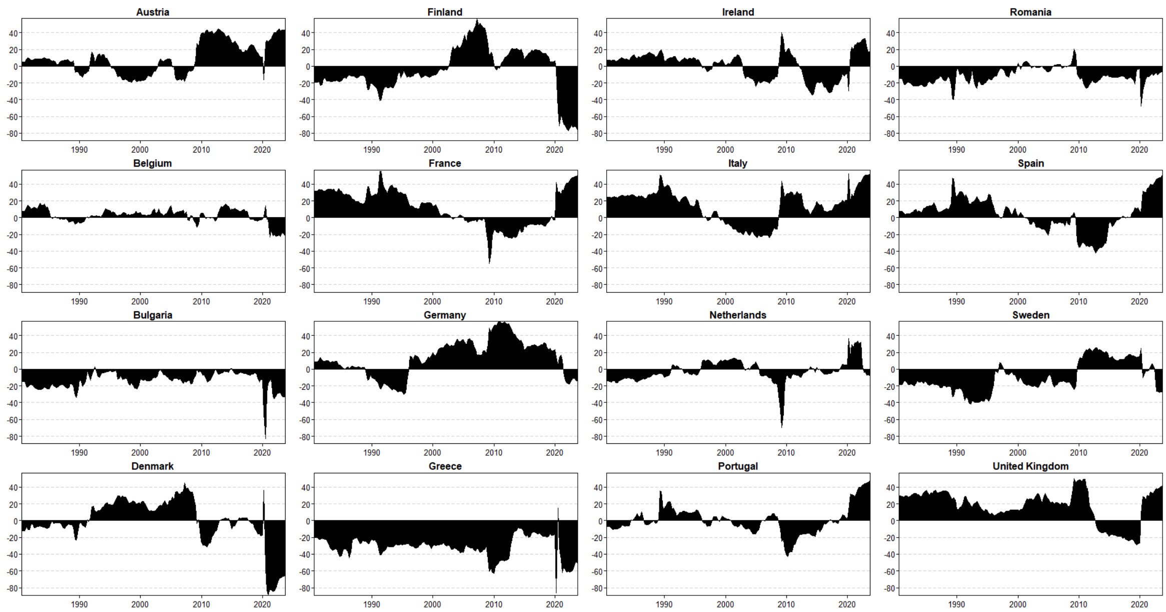
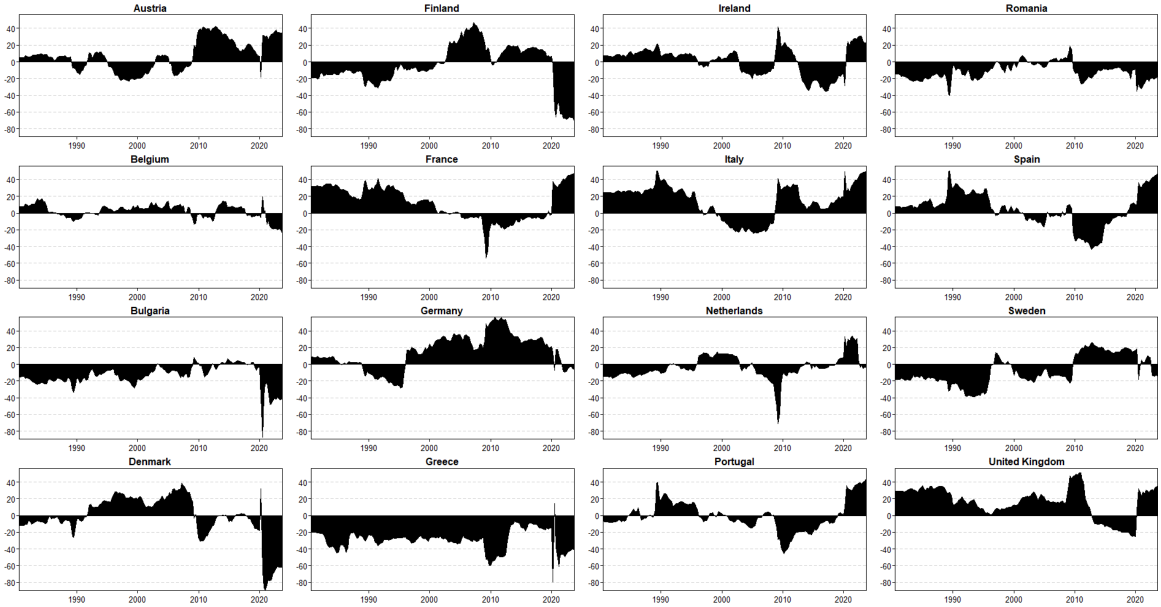


Figure 7

Net directional total connectedness across 16 EU countries (horizon = 8)



Conclusion

In contrast to previous studies using spatial techniques and methods based on the DY methodology, to the best of our knowledge, our study is the first to apply the methodology introduced by Antonakakis et al. (2020) to EU countries using quarterly CO_2 emissions data. The EU countries are of great significance as they are at the forefront of the global climate and energy crises, with the capacity to influence environmental issues globally. Accordingly, we analysed the spillover effects and dynamic connectedness measures of 16 EU countries.

Our findings indicate that the UK, Germany, Italy, and France have the highest spillover effects on other countries. Given that these countries also have the highest CO_2 emissions, this finding is important and interesting. Regarding net connectedness measures, Germany and the UK are the primary CO_2 transmitters, whereas Greece and Bulgaria are the main receivers. These findings align with prior studies showing that CO_2 emissions and economic growth move simultaneously over the business cycle, indicating that higher-income countries tend to contribute more to pollution spillovers, whereas lower-income countries tend to suffer more from them.The dynamic connectedness between pairs of countries also reveals that the closer countries are geographically, the more interconnected they tend to be.

These findings have four significant policy consequences. First, they indicate that environmental problems are not confined to one country and cannot be solved in isolation due to spillover effects among countries. This conclusion is also supported by the United Nations, which maintains that addressing climate change requires an unprecedented level of global cooperation. Therefore, countries must question their economic models, invent new industries, and value nature far beyond money to force rich nations to recognise their moral responsibility to the rest of the world (United Nations, 2021). Due to the existence of spillover effects, EU countries should collaborate in developing carbon mitigation technologies, share the associated costs, and provide incentives to firms or member countries that develop patents to address environmental issues while also raising the expenses linked to higher emissions.

Second, as higher-income countries are the primary pollution transmitters, there may exist a trade-off between economic growth and environmental preservation. However, sustainable development necessitates economic progress and environmental protection. Therefore, it is critical to decouple growth from environmental degradation at this juncture, as emphasised in the 8th Sustainable Development Goal (UNDP, 2023). To ensure environmental protection, EU countries must strive to achieve the goal of increasing the share of renewables and completely phasing out nonrenewable sources as soon as possible. For net transmitter countries, particularly Germany, the UK, Italy, and France, climate policy should place greater emphasis on stricter emission reduction targets within the framework of the EU Emissions Trading System, more effective carbon pricing schemes, and stronger regulatory frameworks. Owing to their higher economic capacity and substantial contribution to cross-border spillovers, these countries are well positioned to take a leading role in financing, developing, and disseminating clean energy technologies across the EU. By contrast, net receiver countries, such as Greece and Bulgaria, require policy measures aimed at mitigating the adverse effects of externally generated pollution spillovers. In these cases, EU-level financial support, particularly through ETS revenues and related funds, along with technology transfer mechanisms and targeted investments in renewable energy infrastructure, is crucial for reducing exposure to externally generated emissions. Implementing such differentiated policy approaches would help address asymmetric spillover dynamics while fostering a more coordinated and effective EU-wide climate strategy. Furthermore, trade instruments, such as the EU's Carbon Border Adjustment Mechanism (CBAM), can serve as important complementary tools. By mitigating carbon leakage and preventing the offshoring of emissions, CBAM safeguards the integrity and impact of the EU's internal decarbonisation efforts.

Third, as connectedness is stronger if countries are closer geographically, these countries must carefully consider the environmental consequences of their actions and policies. Particularly, when developing policies, they should be aware that they affect not only themselves but also neighbouring countries.

Fourth, even though various conferences, summits, and ratified agreements emphasise the key role of international cooperation, such as the EU's inclusion in the Paris Agreement and the Green New Deal, more than mere highlighting is required. Concrete actions are needed, commitments must be taken seriously, and targets must be achieved promptly. Awareness of these points will ensure a sustainable world with a clean environment and economic development.

In this study, only CO_2 emissions were used as a proxy for environmental pollution due to the limited availability of high-frequency data for other indicators. However, carbon emissions only reflect air pollution and ignore soil and water pollution. Moreover, the analysis focuses specifically on mapping the spillover structure of CO_2 emissions rather than identifying their underlying economic drivers. Accordingly, variables such as GDP or energy mix are not included in the empirical model. Future research could extend this framework by incorporating broader environmental measures, such as the ecological footprint, or by directly examining how economic factors influence spillover positions using complementary econometric methods. Finally, future studies could conduct a similar analysis for the top large emitting countries.

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Author Details

Çağla Bucak

[1] Ege University, Faculty of Economics and Administrative Sciences, Department of Economics, İzmir, Türkiye

0000-0003-3169-110X cagla.bucak@ege.edu.tr

A. Nazif Çatık (Prof. Dr.)

[1] Ege University, Faculty of Economics and Administrative Sciences, Department of Economics, İzmir, Türkiye

0000-0001-9247-5668

References

Abdo, A.-B., Li, B., Zhang, X., Lu, J., & Rasheed, A. (2020). Influence of FDI on environmental pollution in selected Arab countries: a spatial econometric analysis perspective. *Environmental Science and Pollution Research,* 27, 28222-28246. https://doi.org/10.1007/s11356-020-08810-4.

Akhundjanov, S., & Muñoz-García, F. (2019). Transboundary Natural Resources, Externalities, and Firm Preferences for Regulation. *Environmental and Resource Economics*, 7, 333–352 https://doi.org/10.1007/s10640-018-0265-5.

Akram, V. (2022). Spillover effect of greenhouse gas emissions across five major continents. *Environmental Science and Pollution Research,* 29, 11634-11643. https://doi.org/10.1007/s11356-021-16535-1.

Al-Silefanee, R. R., Mamkhezri, J., Khezri, M., Karimi, M. S., & Khan, Y. A. (2022). Effect of Islamic financial development on carbon emissions: A spatial econometric analysis. *Frontiers in Environmental Science,* 10, 1-13. https://doi.org/10.3389/fenvs.2022.850273.

Alola A. A., & Bekun F. V. (2021). Pandemic outbreaks (COVID-19) and sectoral carbon emissions in the United States: A spillover effect evidence from Diebold and Yilmaz index. *Energy & Environment,* 32 (5), 945-955. https://doi.org/10.1177/0958305X20977275.

Anscombe, F. J., & Glynn W. J. (1983). Distribution of the kurtosis statistic b2 for normal samples. *Biometrika,* 70 (1), 227-234.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management,* 13 (84). https://doi.org/10.3390/jrfm13040084.

Balsalobre-Lorente, D., Ibáñez-Luzón, L., Usman, M., & Shahbaz, M. (2022). The environmental Kuznets curve, based on the economic complexity, and the pollution haven hypothesis in PIIGS countries. *Renewable Energy,* 185, 1441-1455. https://doi.org/10.1016/j.renene.2021.10.059.

Barrett, S. (1994). Self-Enforcing International Environmental Agreements. Oxford Economic Papers, 46, 878-894.

Cohen, G., Jalles, J. T., Loungani, P., Pizzuto, P. (2022). Trends and cycles in CO2 emissions and incomes: Cross-country evidence on decoupling. *Journal of Macroeconomics,* 71(103397). https://doi.org/10.1016/j.jmacro.2022.103397.

Crippa, M., Guizzardi, D., Banja, M., Solazzo, E., Muntean, M., Schaaf, E. ... Vignati, E. (2022). CO_2 emissions of all world countries. *EU Publications.* https://doi.org/10.2760/730164.

D'Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. *Biometrika,* 57 (3), 679-681.

Declercq, B., Delarue, E., & D'haeseleer, W. (2011). Impact of the economic recession on the European power sector's CO_2 emissions. *Energy Policy,* 39, 1677–1686. https://doi.org/10.1016/j.enpol.2010.12.043.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal,* 119, 158-171. https://doi.org/10.1111/j.1468-0297.2008.02208.x.

Diebold, F. X. & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting,* 28, 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Diebold, F. X. & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics,* 182, 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012.

Doda, B. (2014). Evidence on business cycles and CO_2 emissions. *Journal of Macroeconomics,* 40, 214-227. http://dx.doi.org/10.1016/j.jmacro.2014.01.003.

Doğan, B., Driha, O. M., Balsalobre Lorente, D., & Shahzad, U. (2021). The mitigating effects of economic complexity and renewable energy on carbon emissions in developed countries. *Sustainable Development,* 29, 1-12. https://doi.org/10.1002/sd.2125.

European Commission. (2020). Delivering the European Green Deal. [Retrieved 2023-09-18] Available at: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/delivering-european-green-deal_en.

Fisher, T. J. & Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association,* 107 (498), 777-787. https://doi.org/10.1080/01621459.2012.688465.

Gu, W., Chu, Z., & Wang, C. (2020). How do different types of energy technological progress affect regional carbon intensity? A spatial panel approach. *Environmental Science and Pollution Research,* 27, 44494-44509. https://doi.org/10.1007/s11356-020-10327-9.

Ha, L. T. (2023). Scrutinizing interlinkages between digitalization, economic complexity, green technologies, green energy consumption and CO_2 emission by quantile spillovers in Vietnam. *Environmental Science and Pollution Research,* 30, 81073-81092. https://doi.org/10.1007/s11356-023-28114-7.

He, K., Ramzan, M., Awosusi, A. A., Ahmed, Z., Ahmad, M., & Altuntaş, M. (2021). Does globalization moderate the effect of economic complexity on CO_2 emissions? Evidence from the top 10 energy transition economies. *Frontiers in Environmental Science,* 9 (778088). https://doi.org/10.3389/fenvs.2021.778088.

Jarque, C. M., & Bera, A. K. (1980). "Efficient tests for normality, homoscedasticity and serial ındependence of regression residuals." *Economics Letters,* 6, 255-259.

Jawadi, F., Rozin, P., & Bourghelle, D. (2023). Insights into CO_2 emissions in Europe in the context of COVID-19: A panel data analysis. *International Economics,* 173, 164-174. https://doi.org/10.1016/j.inteco.2022.11.006.

Jebabli, I., Lahiani, A., & Mefteh-Wali, S. (2023). Quantile connectedness between CO_2 emissions and economic growth in G7 countries. *Resources Policy,* 81 (103348). https://doi.org/10.1016/j.resourpol.2023.103348.

Jeetoo, J., & Chinyanga, E. R. (2023). A spatial econometric analysis of the environment Kuznets curve and pollution haven hypothesis in Sub-Saharan Africa. *Environmental Science and Pollution Research,* 30, 58169-58188. https://doi.org/10.1007/s11356-023-26306-9.

Kanas, A., Molyneux, P., & Zervopoulos, P. D. (2023). Systemic risk and CO_2 emissions in the U.S. *Journal of Financial Stability,* 64 (101088). https://doi.org/10.1016/j.jfs.2022.101088.

Karimi, M. S., Khezri, M., Khan, Y. A., & Razzaghi, S. (2022). Exploring the influence of economic freedom index on fishing grounds footprint in environmental Kuznets curve framework through spatial econometrics technique: evidence from Asia-Pacific countries. *Environmental Science and Pollution Research,* 29, 6251-6266. https://doi.org/10.1007/s11356-021-16110-8.

Li, J., & Li, S. (2020). Energy investment, economic growth and carbon emissions in China-Empirical analysis based on spatial Durbin model. *Energy Policy,* 140 (111425). https://doi.org/10.1016/j.enpol.2020.111425.

Li, K., Fang, L., & He, L. (2019). The impact of energy price on CO_2 emissions in China: A spatial econometric analysis. *Science of the Total Environment,* 706 (135942). https://doi.org/10.1016/j.scitotenv.2019.135942

Li, Z., & Wang, J. (2022). Spatial spillover effect of carbon emission trading on carbon emission reduction: Empirical data from pilot regions in China. *Energy,* 251 (123906). https://doi.org/10.1016/j.energy.2022.123906.

Libecap, G. D. (2013). Addressing Global Environmental Externalities: Transaction Costs Considerations. NBER Working Paper No. 19501.

Lin, H., Wang, X., Bao, G., & Xiao, H. (2022). Heterogeneous Spatial Effects of FDI on CO_2 Emissions in China. *Earth's Future,* 10. https://doi.org/10.1029/2021EF002331.

Mbarek, M. B., Ali, N. B., & Feki, R. (2014). Causality relationship between CO_2 emissions, GDP and energy intensity in Tunisia. *Environment, Development and Sustainability,* 16, 1253-1262. https://doi.org/10.1007/s10668-014-9525-x.

Murshed, M., Nurmakhanova, M., Elheddad, M., & Ahmed, R. (2020). Value addition in the services sector and its heterogeneous impacts on CO_2 emissions: revisiting the EKC hypothesis for the OPEC using panel spatial estimation techniques. *Environmental Science and Pollution Research,* 27, 38951-38973. https://doi.org/10.1007/s11356-020-09593-4.

Nguyen, X. P., Hoang, A. T., Ölçer, A. I., & Huynh, T. T. (2021). Record decline in global CO_2 emissions prompted by COVID-19 pandemic and its implications on future climate change policies. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects,* 1-4. https://doi.org/10.1080/15567036.2021.1879969.

Pagnottoni P. (2023). Superhighways and roads of multivariate time series shock transmission: Application to cryptocurrency, carbon emission and energy prices. *Physica A,* 615 (128581). https://doi.org/10.1016/j.physa.2023.128581.

Pea-Assounga, J. B. B., & Wu, M. (2022). Impact of financial development and renewable energy consumption on environmental sustainability: a spatial analysis in CEMAC countries. *Environmental Science and Pollution Research,* 29, 58341-58359. https://doi.org/10.1007/s11356-022-19972-8.

Peng, G., Meng, F., Ahmed, Z., Ahmad, M., & Kurbonov, K. (2022). Economic growth, technology, and CO_2 emissions in BRICS: Investigating the non-linear impacts of economic complexity. *Environmental Science and Pollution Research,* 29, 68051-68062. https://doi.org/10.1007/s11356-022-20647-7.

Peters, G. P., Marland, G., Quéré, C. Le, Boden, T., Canadell, J. G., & Raupach, M. R. (2012). Rapid growth in CO2 emissions after the 2008-2009 global financial crisis. *In Nature Climate Change,* 2, 2-4. https://doi.org/10.1038/nclimate1332.

Quéré, C. Le, Peters, G. P., Friedlingstein, P., Andrew, R. M., Canadell, J. G., Davis, S. J., Jackson, R. B., & Jones, M. W. (2021). Fossil CO_2 emissions in the post-COVID-19 era. *Nature Climate Change,* 11, 197-199. https://doi.org/10.1038/s41558-021-01001-0.

Qunfang, G., & Huang, X. (2023). The influence of energy consumption and research and development on carbon emission in China: a modified spatial Durbin model approach. *Environmental Science and Pollution Research,* 30, 44173-44186. https://doi.org/10.1007/s11356-023-25429-3.

Radmehr, R., Henneberry, S. R., & Shayanmehr, S. (2021). Renewable energy consumption, CO_2 emissions, and economic growth nexus: A simultaneity spatial modeling analysis of EU countries. *Structural Change and Economic Dynamics,* 57, 13-27. https://doi.org/10.1016/j.strueco.2021.01.006.

Refinitiv Eikon Datastream. 2023. [Retrieved 2023-08-23] Available at: https://www.refinitiv.com/en/products/datastream-macroeconomic-analysis.

Ren, X., Cheng, C., Wang, Z., & Yan, C. (2020). Spillover and dynamic effects of energy transition and economic growth on carbon dioxide emissions for the European Union: A dynamic spatial panel model. *Sustainable Development,* 1-15. https://doi.org/10.1002/sd.2144.

Shahnazi, R., & Shabani, Z. D. (2021). The effects of renewable energy, spatial spillover of CO_2 emissions and economic freedom on CO_2 emissions in the EU. *Renewable Energy,* 169, 293-307. https://doi.org/10.1016/j.renene.2021.01.016.

Shirazi, M. & Šimurina, J. (2022). Dynamic behavioral characteristics of carbon dioxide emissions from energy consumption: the role of shale technology. *Environmental Science and Pollution Research,* 29, 28829-28853. https://doi.org/10.1007/s11356-021-18352-y.

Tawfeeq, M. (2023). The spillover impacts of urbanization and energy usage on CO_2 emissions: A regional analysis in the United States. *Energy Exploration & Exploitation,* 0(0), 1-16. https://doi.org/10.1177/01445987231158145.

UNDP. (2023). Sustainable Development Goals. [Retrieved 2023-07-15] Available at: https://www.undp.org/sustainable-development-goals.

United Nations. (2021). Climate change 'biggest threat modern humans have ever faced', world-renowned naturalist tells security council, calls for greater global cooperation. [Retrieved 2023-09-15] Available at: https://press.un.org/en/2021/sc14445.doc.htm.

United Nations. (2023). For a livable climate: Net-zero commitments must be backed by credible action. [Retrieved 2023-09-12] Available at:. https://www.un.org/en/climatechange/net-zero-coalition.

Vo, D. H. & Vo, L. H. (2022). International volatility transmission among income, CO_2 emission, non-renewable and renewable energy consumption: Which causes which and when? *Energy Reports,* 8: 10061-10071. https://doi.org/10.1016/j.egyr.2022.07.168.

Wen, Q., Chen, Y., Hong, J., Chen, Y., Ni, D., & Shen, Q. (2020). Spillover effect of technological innovation on CO_2 emissions in China's construction industry. *Building and Environment,* 171 (106653). https://doi.org/10.1016//j.buildenv.2020.106653.

Wu, J., Abban, O. J., Boadi, A. D., & Charles, O. (2022). The effects of energy price, spatial spillover of CO_2 emissions, and economic freedom on CO_2 emissions in Europe: a spatial econometrics approach. *Environmental Science and Pollution Research,* 29, 63782-63798. https://doi.org/10.1007/s11356-022-20179-0.

You, W., & Lv, Z. (2018). Spillover effects of economic globalization on CO_2 emissions: A spatial panel approach. *Energy Economics,* 73, 248-257. https://doi.org/10.1016/j.eneco.2018.05.016.

Zhang, D., Chen, X. H., Lau, C. K. M., & Xu, B. (2023). Implications of cryptocurrency energy usage on climate change. *Technological Forecasting & Social Change,* 187 (122219). https://doi.org/10.1016/j.techfore.2022.122219.

Zhang, G., Zhang, N., & Liao, W. (2018). How do population and land urbanization affect CO2 emissions under gravity center change? A spatial econometric analysis" *Journal of Cleaner Production,* 202, 510-523. https://doi.org/10.1016/j.jclepro.2018.08.146.

Zhang, Q., Yang, J., Sun, Z., & Wu, F. (2017). Analyzing the impact factors of energy-related CO_2 emissions in China: What can spatial panel regressions tell us? *Journal of Cleaner Production,* 161, 1085-1093. https://doi.org/10.1016/j.jclepro.2017.05.071.