1. Introduction

In today's interconnected world, the significance of uncertainty within economic policy decisions has reached unprecedented levels. This can be attributed to the complex interplay of global economic forces, geopolitical factors, rapid technological advancements, and the increasing interconnectedness of economies across borders. As a result, policymakers and stakeholders face a landscape where the implications of economic policy choices ripple far beyond national borders and have profound consequences on a global scale. This intricate web of interactions amplifies the need for a deeper understanding of the multifaceted nature of policy uncertainty, as its impact extends, not only to economic outcomes, but also to various aspects of society, environment and international relations.

Currently, the economic policy regime in most modern states is characterised by strong uncertainty stemming from various critical situations, all with implications for the ongoing climate challenge: the Ukrainian conflict (Selmey and Elamer, 2023), the covid-19 pandemic (Chen et al., 2023), increasingly frequent extreme weather events, like heatwaves and floods (Agnello et al., 2020), uncontrollable inflation (Wei et al., 2021), strained international trade relations among superpowers (Hu et al., 2023), protective industrial policies for strategic assets and resources (Zhu et al., 2021), geopolitical tensions (Ivanovski and Marinucci, 2021), widespread economic sanctions (Balsalobre-Lorente et al., 2023), supply chain disruptions (Shahzad et al., 2023), and more. These challenges are further compounded by internal instability within countries, which, in turn, influences the overall economic situation and climate policy stringency.

No doubt economic policy uncertainty (EPU) plays a crucial role for the countries' energy transformation, particularly for those countries committed to combating climate change and transitioning to renewable energy sources, replacing fossil fuels. In the literature, attention has primarily focused on the effects resulting from EPU on carbon dioxide emissions (Hussain et al., 2023; Yu et al., 2021). Still, there are very few contributions that have provided evidence on the underlying mechanisms through which these two variables are intertwined.

EPU may affect carbon emissions through different channels. Economic uncertainty could divert governments' attention from energy issues and related environmental problems, reducing their ability to speed up the transition and negatively affecting the resulting aggregate environmental performance (Amin and Dogan, 2021; Jiang et al., 2019a). However, it is worth noting that the climate challenge is now a top priority on the political agenda of many countries, with remarkable results achieved over the past decade (although not yet sufficient to meet the targets set by the 2015 Paris Agreement).

Several studies suggest that increased uncertainty negatively impacts firms' economic performances, reducing the energy consumption required for their productive activities. This would support the thesis that higher uncertainty may correspond to lower energy demand and more moderate CO_2 emissions (Adedoyin and Zakari, 2020; Adedoyin et al., 2021; Ahmed et al., 2021). However, this thesis is not fully confirmed in the literature, with many contributions highlighting contrasting results, according to which raising uncertainty would increase emissions (Amin and Dogan, 2021; Yu et al., 2021; Zhou et al., 2022). Accordingly, economic uncertainty could undermine financial sustainability and reduce the ability to invest in clean or 'green' technologies, such as renewable technologies, which are usually more expensive and complex to adopt than 'brown' or 'grey' ones (Adedoyin and Zakari, 2020; Jiang et al., 2019; Shafiullah et al., 2021). Nonetheless, increased EPU often coincides with higher oil prices (Ilyas et al., 2021; Qin et al., 2020), a phenomenon that may impact positively on investments in green or renewable energy technologies, followed by lower CO_2 emissions (Liu et al., 2020).

The purpose of this paper is to address the following question: does EPU impact the climate challenge? Answering this question is relevant in times characterised by high uncertainties and pressing climate change. The literature focusing on the relationship between EPU and renewable energy is relatively scant (Ivanovski and Marinucci, 2021; Shafiullah et al., 2021). Results are mixed, with some studies suggesting a negative relationship, where EPU would reduce investments in renewables (Adedoyin and Zakari, 2020), while others arguing for a positive impact, where EPU drives up the price of fossil fuels and incentivises renewables (Chu and Le, 2022; Liu et al., 2020). Others assume that the relationship between EPU and investments in renewable energy may take the form of an inverted U-shape (Lin and Li, 2022).

We employ a panel regression approach based on different models, incorporating additional dimensions to account, as much as possible, for the socio-technical regime, which encompasses all those variables generating some influence on the 'core' relationship between EPU and renewable energy production. Nowadays, the energy transition needs to be embedded within the economic, regulatory, technological, political and social dimensions (Andrews-Speed, 2016). We choose the variables representing the socio-technical regime, in line with the literature: climate policy, energy intensity as a proxy for national energy demand, research, development, and deployment (RD&D) expenditures in energy technologies, imports of renewable technologies as a proxy for external knowledge, national wealth and carbon dioxide emissions. Furthermore, we explain country heterogeneity through diverse partitions.

Using data from over 15 countries, we adopt a two-step empirical strategy. Firstly, we test panel regression models, according to which EPU impacts positively on the climate challenge, with other socio-technical variables showing significant coefficients with the expected sign. All things considered, in the last decades, governments have chosen to commit more to renewables when fossil fuel prices are high, as a way-out from the current uncertainties and given higher returns on investments in terms of energy security, economic system resilience and green transition.

Additionally, the paper focuses on the spillover effects between countries, exploring partitions based on the European Union (EU) and trade connections. Accordingly, we build a 'trade' space in which EPU and all other variables can spill over national borders to indirectly influence the policy choices of economic partners, in line with an emerging literature (Jiang et al., 2019b; Wang et al., 2023; Yu et al., 2021). Firms' choices and governments' actions are the result of interdependent forces acting within a complex system where the policies, resources and needs of economic partners tend to transcend national boundaries and affect neighbours' choices and long-term strategies. We propose different models to account for these dependencies: the analysis appreciates the strong economic interconnections between countries and tests the consistency of most results, especially with regards to the EU.

The contributions of the paper to the existing literature are twofold. First, the paper aims to contribute to investigating the role of EPU in the climate challenge by focusing specifically on a major 'upstream' mechanism that is based on renewable energy production: if EPU impacts positively on renewables, this would help to reduce emissions and advance the energy transition. Secondly, given the prevalent consensus that uncertainty generates spillover effects on other countries, the paper focuses not only on the direct impact exerted by climate policies and the domestic socio-technical determinants of renewable energy, but also on the contribution that economic partners make to a country's policy choices, filling in the gaps and distractions that ‘pro tempore’ governments may have towards the climate challenge.

By exploring these dynamics, this paper contributes to a better understanding of the intricate relationships between economic uncertainty and the climate challenge, offering valuable insights for policymakers and researchers alike.

The paper is organized as follows. Section 2 reviews the literature and theoretical mechanisms linking EPU with environmental and energy outcomes. Specifically, Section 2.1 discusses how EPU can influence carbon emissions, Section 2.2 examines the relationship between EPU and the climate challenge, and Section 2.3 explores the role of EPU in cross-country spillovers. Section 3 describes the dataset, detailing the sources and characteristics of the variables used in the analysis. Section 4 presents methodology and results: Section 4.1 introduces the panel data regression models, Section 4.2 describes spatial regression models that capture the influence of the covariates across trade partners, Section 4.3 focuses on the EU, and Section 4.4 considers alternative measures of climate policy stringency. Section 5 concludes the paper, highlighting key findings, presenting limitations, and discussing policy implications.

2. Literature

2.1. On economic policy uncertainty and CO_2 emissions

The literature on the role of EPU in the climate challenge has focused primarily on the effects on carbon dioxide emissions.

Hussain et al. (2023) explore the influence of EPU on carbon emissions in the five most polluted economies in the world. The results reveal that EPU has a detrimental effect on the environment, while other factors such as renewable energy consumption and natural resources significantly contribute to reducing emissions. Similar results have been attained by Durani et al. (2023). Yu et al. (2021) show, based on data from Chinese manufacturing firms, an adverse impact of EPU on firms’ carbon emission intensity. Interestingly, this influence is primarily channelled through a higher reliance on fossil fuels in the short term, rather than firms’ innovation.

All the above-mentioned findings emphasize the role that a rising EPU may play in hindering a country’s emission reduction efforts. Nonetheless, studies investigating the intricate pathways linking EPU and emissions are scarce. EPU’s influence on carbon emissions is multi-faceted. Economic uncertainty has the potential to shift governments’ focus away from energy concerns and associated environmental challenges. This diversion can diminish their capacity to expedite the renewable energy transition, thereby adversely impacting overall environmental outcomes (Amin and Dogan, 2021; Jiang et al., 2019a).

Several studies suggest that increased uncertainty negatively impacts firms’ economic performance, reducing the energy consumption required for their productive activities (Adedoyin and Zakari, 2020; Adedoyin et al., 2021; Ahmed et al., 2021). This would support the thesis that higher uncertainty may correspond to lower energy demand and, consequently, more moderate emissions (Amin and Dogan, 2021; Yu et al., 2021). Zhou et al. (2022) study the impact of renewable energy, environmental technologies and EPU on carbon emissions. The results highlight the detrimental effect of EPU on emissions, while renewable energy and environmental technologies play a supportive role.

Some scholars find that economic uncertainty may erode financial stability and limit investments in environmentally friendly or ‘green’ technologies, like renewable energy solutions, which tend to be more costly and intricate to implement compared to ‘brown’ or ‘grey’ alternatives (Adedoyin and Zakari, 2020; Jiang et al., 2019a; Shafiullah et al., 2021). Nevertheless, it is worth noting that higher EPU often coincides with rising oil prices, which could potentially incentivize investments in green or renewable energy technologies, resulting in decreased carbon emissions (Ilyas et al., 2021; Liu et al., 2020; Qin et al., 2020).

2.2. On economic policy uncertainty and renewable energy production

The literature that specifically examines the connection between EPU and renewable energy production is limited (Ivanovski and Marinucci, 2021; Shafiullah et al., 2021).

A few studies contend that higher EPU can stimulate renewable energy production, by raising fossil fuel prices (Chu and Le, 2022; Liu et al., 2020). Alternatively, some scholars suggest that the relationship between EPU and renewable energy investments follows a non-linear pattern. Lin and Li (2022) investigate the relationship between EPU and strategic investment in Chinese renewable energy firms. The findings reveal an inverted U-shaped relationship between EPU and strategic investment. This suggests that a moderate level of EPU may encourage strategic investment in this sector, but excessive uncertainty could work as a deterrent. This is in line with Chen et al. (2019) and Sarkar (2000).

Accordingly, we introduce our first research question:

> *RQ#1: Controlling for the socio-technical regime, does economic policy uncertainty hinder the production of renewable energy?*

2.3. On economic policy uncertainty and cross-country spillovers

If we acknowledge that a country’s ability to lead the energy transition depends on various factors like economic uncertainty, policy stringency, energy demands and available resources, we must also recognize that countries do not operate in isolation. Many argue that these spillover effects exert a profound influence on policy choices, budget allocations and long-term trajectories, often outweighing political party affiliations or austerity measures aimed at fiscal consolidation (Colombo, 2013; Wang et al., 2023).

Although such interdependencies are most easily discernible in the spillover effects generated on industrial prices, stock market returns and energy markets, no less negligible are those that take place in trade relations between countries (Balli et al., 2017; Klößner and Sekkel, 2014; Trung, 2019). The expected results on the role of spillover effects are in line with several contributions on technology spillovers in the energy field (Ho et al., 2018; Huang et al., 2020; Verdolini and Galeotti, 2011). Although more contained in the proposed applications, policy or regulatory spillovers have also been investigated in the literature and the insights are of interest (Costantini et al., 2017; Liu et al., 2022).

In line with the above literature, we introduce our second research question:

> *RQ#2: Since countries are economically intertwined, do EPU and socio-technical regimes generate spillovers that impact neighbours' renewable energy transition?*

3. Data

We propose a conceptual framework based upon several variables, in line with the relevant literature. These include: share of electricity production from renewables (REP), economic policy uncertainty index (EPU), environmental policy stringency index (EPS), energy intensity (measured as tonnes of oil equivalent per thousand 2005 US dollars of GDP calculated using PPPs, INT), energy technology RD&D expenditures (energy technology RD&D budgets, per thousand units of GDP, RDD), import of solar and wind technologies (share of GDP, in thousands of current US dollars, IMP), GDP per capita (constant 2015 US$, GDP), and carbon dioxide emissions (metric tons per capita, CO2).

REP serves as our dependent variable, in line with a vast literature (Bourcet, 2020). To measure EPU, we employ the index developed by Baker et al. (2016), which is calculated on the frequency of specific terms such as "economic", "policy", and "uncertainty" in national newspapers. This metric effectively reflects the current level of uncertainty surrounding economic policies, as depicted by the media.

To evaluate the role of climate policy, we use a nationally applicable index that allows for international comparison of policy stringency, where ‘stringency’ signifies the extent to which policies impose explicit or implicit costs on environmentally detrimental activities. This metric spans a spectrum from 0 to 6 (indicating, respectively, a lack of stringency and the utmost stringency) and is constructed based on 14 policy instruments, predominantly addressing climate and air pollution concerns (Botta and Koźluk, 2014; de Serres et al., 2010). EPS is the primary variable representing the socio-technical regime and is expected to positively influence REP. Athari (2024) explores the influence of EPS on renewable energy consumption within OECD countries, and investigates whether EPS can mediate the relationship between EPU and the adoption of renewable energy sources. Results show that EPS has a positive impact on renewables and a beneficial role in lessening the negative effect of EPU.

All other variables contribute to build the relevant regime. These, and their relative interpretation, are self-explanatory.

A reduction in energy intensity is expected to promote the renewable energy development, facilitating significant steps in energy conservation and diminished consumption by eliminating outdated technologies (Zhang et al., 2011). RD&D budgets are being committed to energy technology work as a proxy for evaluating the technological trajectory in the energy field. Ensuring public support to the technological side of the energy transition is a key prerequisite, serving as a catalyst to propel innovation (Alvarez-Herranz et al., 2017). In line with Verdolini and Galeotti (2011), we encompass ‘external’ knowledge, using imports of solar and wind technologies (IMP) according to a specific taxonomy. Such a perspective, coupled with the ‘internal’ knowledge pertaining to RDD, is based on the consideration that the convergence of these two knowledge streams may exert a positive influence on the renewable energy transition. Gross domestic product (GDP) per capita is the primary economic indicator frequently used in the literature to explain the adoption of renewable energy sources (Sadorsky, 2009). Finally, a bidirectional causal relationship may exist between CO_2 emissions and the adoption of renewable energy sources. The literature discerned that the energy transition contributes to a decline in CO_2 emissions, yet alongside underscores a reciprocal relationship, where carbon emissions impact the speed and trajectory of the climate challenge (Marra and Colantonio, 2022). This inference implies that strategies enacted by countries to mitigate emissions inherently necessitate the incorporation of cleaner energy sources.

Within this conceptual framework, we aim to investigate REP drivers in Australia, Brazil, Canada, France, Germany, Greece, Ireland, Italy, Japan, Korea, Netherlands, Spain, Sweden, United Kingdom and the United States. Initially, 22 countries were identified with available data for the EPU variable. However, Mexico and Singapore were subsequently excluded due to a lack of data on the EPS variable; China, India and Russia were also excluded due to a lack of data on the RDD variable; and Chile and Colombia, due to a lack of data on both the EPS and RDD variables. We use the longest time span possible from 1994 to 2021.

Table 1 presents the names of the variables, their definitions, and sources.

Table 1. Variables description.

The descriptive statistics for the variables are shown in Table 2.

Table 2. Descriptive statistics.

Table 2 presents the mean values, standard deviations, and the maximum and minimum recorded observations. Notably, the share of electricity production from renewable sources (REP) has an average of 25.481 and a maximum of 95.406. In general, significant volatility between the minimum and maximum values is evident across all variables.

4. Methods and results

For the empirical analysis, several spatial models were tested, with a non-spatial model initially introduced as a benchmark.

4.1. Panel data regressions

First, the study employs a panel regression model to examine the influence of several possible key factors on the production of electricity from renewable sources. Using REP as the dependent variable, the panel regression model is defined as follows:

$$REP_{it} = \beta_0 + \beta_1 EPU_{it-1} + \beta_2 EPS_{it-1} + \beta_3 INT_{it-1} + \beta_4 RDD_{it-1} + \beta_5 IMP_{it-1} + \beta_6 GDP_{it-1} + \beta_7 CO2_{it-1} + \varepsilon_{it} \quad (1)$$

In Equation (1), countries are represented by the subscript i (i = 1, …, N), the subscript t (t = 1, …, T) specifies the year, the $\beta_0 \sim \beta_7$ represents the corresponding regression coefficient and ε_{it} is the random error term. Since the effects of a change in an explanatory variable on the dependent variable are usually not immediate, an annual time lag is introduced on each independent variable.

A fixed-effects (FE) model and a random-effects (RE) model were established. Note that in Equation (1) FE and RE are omitted. Estimates are reported in Table 3. The optimal regression model was determined through the application of the Hausman test, which indicates that the RE model emerges as the most suitable.

Table 3. Estimation results of linear panel regression.

An increase in EPU produces a positive impact on REP. As seen above, the uncertainty of economic policy may influence investment decisions and emphasise systemic risks. Moreover, a higher level of EPU is associated with an elevated likelihood of bankruptcy, leading to increased external financing costs, which lower the propensity to invest. Nonetheless, renewable energy companies seem to be less exposed, compared to non-renewable ones, given their early stage of development and high-growth potential. To notice that EPU positively correlates to fossil fuel prices, thereby fostering REP and acting as a deterrent to investments in non-green (or brown) energy industries (Liu et al., 2020). Accordingly, a rise in EPU can be associated with a larger proportion of electricity generated from renewable sources.

As expected, the socio-technical regime is supportive (Marra and Colantonio, 2023). At least in this preliminary specification, EPS exerts a positive influence on REP (Athari, 2024). Governments need an array of policy interventions. By fostering the advancement of clean technologies while restricting investments in dirty ones, climate policy has a huge potential (Du et al., 2021; Ouyang et al., 2020).

An increase in energy intensity should stimulate a reaction in the adoption of new energy solutions, with a subsequent positive influence on REP. Setting stringent targets in terms of INT plays a pivotal role in fostering renewables and phasing out non-renewable ones (Wang and Liu, 2018; Zhang et al., 2019). While less developed countries are used to set relatively modest targets, modern countries are more ambitious and are able to use subsidies, loans and tax incentives (Bai et al., 2021; Li et al., 2014).

The expected and positive impact of the energy technology RD&D expenditure is confirmed (Ardito et al., 2019). RDD may provide new market opportunities related to renewable sources and further technological prospects based on cost reduction and learning by doing.

IMP positively influences REP: external knowledge typically exerts a boost on the trajectory of advancements and innovations in the energy sector (Ogura, 2020). Given weak or constrained domestic production capabilities, countries commonly import green products and technologies from more developed counterparts. This strategy is undertaken to meet internal demand and provide the technological assets necessary to increase the share of electricity produced from renewable sources. The increased variety of imported environmentally sustainable products also holds the potential to foster innovation by broadening the spectrum of available technologies (Chen et al., 2017). Moreover, firms within the importing country may opt to undertake imitative innovation (Damijan and Kostevc, 2015; Liu and Buck, 2007).

Higher levels of GDP are associated with more REP (Sadorsky, 2009). Specifically, two reasons explain how the GDP expansion can favour the expansion of REP. Firstly, economic growth brings more resources for the implementation and promotion of renewable energy initiatives. Secondly, increases in income level imply an augmented capacity to bear the associated policy costs (Chang et al., 2009).

Finally, a reduction in CO2 seems to favour the establishment of a virtuous circle towards a faster green transition. Even though numerous studies have investigated the factors influencing carbon emissions, much less explored is the inverse link between CO_2 emissions and the climate challenge.

4.2. Spatial regression models

The empirical literature suggests the existence of spatial effects between economically close countries, advocating their incorporation into more comprehensive analytical frames.

As is well known, an established statistical measure employed for investigating the presence of spatial autocorrelation is Moran's *I*. We examine the spatial autocorrelation effect in the selected countries by employing the global Moran's I_t for a specific year *t*:

$$I_t = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

where *n* is the number of countries, x_i and x_j represent the *X* of country *i* and country *j*, $\bar{x}$ and s^2 are the mean and variance of *x*, and w_{ij} is the generic element of a $n \times n$ order spatial weight matrix *W*. The literature concerning the specification of *W* is extensive, and various methodological approaches can be used to construct it (Halleck Vega and Elhorst, 2015). One of the most commonly employed methods involves an exogenously determined *W* with fixed weights (row-normalized such that each row of *W* is scaled to sum to one). Specifically, w_{ij} is as follows:

$$w_{ij} = \begin{cases} 0, i = j \\ \sigma_{ij}, i \neq j \end{cases}$$

where σ_{ij} is the similarity between country *i* and country *j*. Since bilateral factors such as trade relationships play a key role in influencing the magnitude of EPU spillovers (Balli et al., 2017), in our case the similarity is based on the average of the values of trade flows between partner countries in the last 5 years, between 2017 and 2021. Data have been collected from the United Nations Comtrade database.

Table 4 shows the global Moran's *I* for years 1994, 2008 and 2021.

Table 4. Global Moran's I statistic.

The results of the Moran's I_t range from [0, 1]. Test statistics are significant for INT and CO2, indicating that energy intensity and carbon emissions exhibit spatial autocorrelation among commercially connected countries. This suggests that analyses neglecting spatial interdependence may yield biased estimates (Westlund, 2013). Four spatial econometric models that systematically incorporate spatial interdependencies were compared (Elhorst, 2010 and 2014). The Spatial Lag Model (SLM), also referred to as the Spatial Autoregressive Model, accounts for spatial interdependence in the dependent variable. This model posits that the value of a given country's dependent variable is influenced by the corresponding values observed in neighbouring countries. Consequently, the dependent variable is estimated also by incorporating the values of the dependent variable from spatially connected countries. The Spatial Error Model (SEM) differs from models incorporating lagged dependent or independent variables, as the spatial interdependencies among units are confined to the error terms. This model implies the presence of an omitted explanatory variable that exhibits spatial correlation. As a result, clusters of spatially correlated values emerge within a country, which are not accounted for by the included predictors. The Spatial Durbin Model (SDM) represents an adaptation of a model first introduced by Durbin (1960) within the framework of time series analysis. Its spatial version incorporates spatial lags in both the dependent and independent variables, making it well-suited to capture externalities and spillover effects that originate from various sources (Anselin, 1988). This model effectively accounts for spatial interactions and dependencies, allowing for a more comprehensive analysis of how influences propagate across spatial units. Finally, the Spatial Durbin Error Model (SDEM) simultaneously introduces spatially lagged explanatory variables and spatial error terms. This model does not contain a lagged dependent variable. For more in-depth discussion, refer to Anselin (1988), LeSage and Pace (2009), and Elhorst (2010 and 2014).

We perform both the classic Lagrange Multiplier (LM) spatial error and spatial lag tests, and their robust counterparts, to evaluate whether a traditional non-spatial panel data model fails to capture relevant spatial interactions within the data, and whether a model with a spatially autocorrelated error term and/or spatial lags of the independent variable would be preferable to the non-spatial model (Debarsy and Ertur, 2010). As highlighted in Table 5, the null hypothesis is commonly rejected at the 1% level of significance, which substantiates the preference for spatial specifications over non-spatial panel data models.

Table 5. Results of spatial dependence diagnostic tests.

The following econometric estimations are based on spatial models under the aegis of random effects. The decision to opt for either a fixed or random effects model is necessary to preclude the derivation of biased parameters that deviate from the intrinsic characteristics of the dataset. Within the literature on environmental degradation using spatial methodologies, various empirical studies employ the specific Hausman test as a substantiation for this selection (Leal et al., 2021; Park and Yun, 2021). Table 6 shows that the random-effect model is most suitable in the explanation of the observed estimates.

Table 6. Hausman test results for spatial models.

Following a Bayesian approach (LeSage and Parent, 2007; LeSage 2014), we compare the four spatial models conditional on the weight matrix W and two *posterior* probabilities (uniform *prior* and beta *prior*). Table 7 shows the results, which seem consistent with preference for the SDEM.

Table 7. Comparison of four spatial econometric models based on two different posterior model probabilities.

The SDEM, which captures the spatially lagged terms of explanatory variables and spatial error terms, is based on the following Equations (2):

$REP_{it} = \beta_0 + \beta_1 EPU_{it-1} + \beta_2 EPS_{it-1} + \beta_3 INT_{it-1} + \beta_4 RDD_{it-1} + \beta_5 IMP_{it-1} + \beta_6 GDP_{it-1} + \beta_7 CO2_{it-} + \delta_1 \sum_j w_{ij} EPU_{jt-1} + \delta_2 \sum_j w_{ij} EPS_{jt-1} + \delta_3 \sum_j w_{ij} INT_{jt-1} + \delta_4 \sum_j w_{ij} RDD_{jt-1} + \delta_5 \sum_j w_{ij} IMP_{jt-1} + \delta_6 \sum_j w_{ij} GDP_{jt-1} + \delta_7 \sum_j w_{ij} CO2_{jt-1} + u_{it}$ (4)

$u_{it} = \rho \sum_j w_{ij} u_{it} + v_{it}$ (2)

The SDEM estimates are shown in Table 8, where φ once more denotes the random effect.

Table 8. SDEM estimation and test results.

Latent variables emanating from commercially connected countries manifest as spatial error terms, exhibiting statistical significance. Furthermore, an exogenous variable's total effect is dissected into direct and indirect effects. The direct effect signifies that variations in the explanatory variables influence the endogenous variable REP. Conversely, the indirect effect elucidates the impact on a focal country's REP due to alterations in the exogenous variables of neighbouring countries. The aggregate of these impacts yields the total effects. In this case, the direct effect denotes that the increase of the endogenous variable (REP) emanates from variations in specific exogenous variables (INT, RDD, IMP, GDP and, inversely, CO2) within a focal country, in line with the predominant literature. Moreover, the spillover (indirect) effect relates to the increase in the response variable resulting from the rise in corresponding exogenous variables in neighbouring countries (excluding RDD).

According to this model, EPU appears to lack a statistically significant influence on renewable electricity production. Both the direct and indirect effects of EPU on renewable electricity production are negligible. This outcome is likely due to the opposing positive and negative impacts of EPU on renewable electricity production, as discussed in the literature.

Lastly, surprisingly, the direct effect of EPS on REP is negative (while the indirect effect is not statistically significant), which seems counterintuitive (Athari, 2024). One potential explanation could be the time delay needed to generate effects. A more stringent climate policy often stimulates RD&D activities, indirectly affecting REP after a certain period. Another possible explanation could be panel heterogeneity: the impacts of environmental policies differ across countries due to various factors, including taxation levels, regulatory measures, policy targets, industrial structure of the economy, interactions with other policies, lobbying activities, and so on (Hassan and Rousselière, 2021).

For completeness, the SEM estimates are also reported in Appendix and confirm the presence of spatial spillovers.

4.3. Analysis on EU countries

Some results of the SDEM seem to be unexpected. In our view, the main reason lies in the heterogeneity that characterizes the entire panel and for this we adopted a rigorous partition, built a more homogeneous sub-panel of countries, and conducted further analysis on the EU members.

EU countries have ambitious goals aimed at achieving carbon neutrality by 2050, coupled with efforts to fortify climate resilience. This underscores the imperative of constraining the escalation of global temperatures within the threshold of 2°C (Billah et al., 2022; Farid et al., 2023). Consequently, the improvement of the capacity to exploit renewable energy sources has seen notable progress. However, substantial untapped potential remains, since the EU energy landscape includes a composite mix of domestically generated energy and imports from non-EU countries (Nunez-Jimenez and De Blasio, 2022). Between 2018 and 2022, on average 41.2% of the energy consumed by EU member states came from national sources, while the remaining 58.8% came from imports (Eurostat, 2024).

We replicated the analysis based on the SDEM on the EU sub-panel to adopt a more comprehensive perspective on spatial spillovers.

In spatial econometrics, the treatment of spatial heterogeneity can be approached from different viewpoints. In this case, we follow a discrete perspective, referred to as spatial regimes, which allow the model coefficients to vary between discrete spatial subsets of the data. We implemented this by creating exogenously a dummy variable for each regime (i.e., taking a value of one for observations in the regime and zero for all others) and then interacted each explanatory variable with each dummy. A Chow test and its extension to spatial regressions (spatial Chow test) allow an assessment of the significance of the regimes. In this case, the spatial Chow test statistic (with a p-value of 0.000) provides evidence of substantial disparities in coefficients across distinct clusters of countries, implying that the proposed partition can be accepted.

The results of the analysis are reported in Table 9.

Table 9. SDEM estimation and test results – EU vs. non-EU countries.

The heterogeneity of countries seems to influence the relationship between variables, as emphasised by the non-significance of many coefficients when examining non-EU countries. Focusing on the EU, four interesting results emerge. Firstly, the direct impact indicates a change in the expected direction of the endogenous variable (REP) due to an increase in exogenous variables (except EPS) within the target country. Secondly, REP in each country is not only influenced by observable factors, including economic policy uncertainty, energy intensity, energy technology R&D budgets, import of solar technologies and wind power, GDP per capita, and CO2 emissions, but also from unobservable factors coming from trade partners (ρ shows a statistically significant value). Thirdly, the (indirect) spillover effect, concerning the change in the response variable, resulting from the increase in exogenous variables coming from neighbouring countries is negligible, except for W EPS.

Finally, the sum of the negative direct and positive indirect effects of EPS gives the ultimate total effects on REP, which are positive (Costantini et al., 2017). The indirect relationship between EPS and REP asks for a more in-depth analysis. When assessing the consequences of environmental policies on REP, it seems that incorporating spatial dimensions would ensure a more comprehensive understanding. Estimations of the spillovers suggest that while these policies effectively promote the adoption of renewable energy resources, they may inadvertently hinder their own energy transition in favour of more virtuous neighbours, corroborating a sort of 'inertia' or free riding: governments sometimes prefer to set a relatively low level of environmental regulation intensity to attract investment, attracting capital and incentivizing local energy projects (Feng et al., 2020).

4.4. Alternative measures of climate policy stringency

There are several indices suitable for measuring climate policy stringency for cross-country comparative analysis. Although EPS has been widely used in the literature as a proxy for climate policy stringency (Bashir et al., 2024; Fatima et al, 2024; Fikru et al., 2024), alternative indicators have been proposed in the literature.

Among these, the Climate Change Performance Index (CCPI), developed by the NewClimate Institute, Germanwatch, and Climate Action Network, measures climate protection performance at the national level based on standardized criteria, incorporating the targets of the Paris Agreement (Burck et al., 2023). Unfortunately, available data for the CCPI start from 2007, and the resulting time series are too short. The Climate Policy Database (CPD) developed by the NewClimate Institute is also an option, but it is rarely used in the literature, and its qualitative approach asks for some discretionary adjustments, which we would prefer to avoid. A possible alternative to EPS is the Climate Actions and Policies Measurement Framework (CAPMF), introduced by Nachtigall et al. (2024). It currently summarizes 130 policy variables, grouped into 56 policy instruments and other climate actions. Compared to EPS or CCPI, the CAPMF covers a much larger number of climate policies, even if it does not provide information on implementation or enforcement, does not reflect policy effectiveness, and may not fully capture the range of a country's climate actions and policies (Nachtigall et al., 2022; 2024).

We therefore decided to replicate the analysis based on the SDEM for the entire panel, excluding the USA and Brazil due to the lack of available data, and the EU sub-panel, using the CAPFM instead of EPS. The results are reported in Tables 10 and 11, respectively.

Table 10. SDEM estimation and test results - CAPMF in place of EPS

Table 11. SDEM estimation and test results – EU vs. non-EU countries. CAPMF in place of EPS.

Although the signs of the coefficients and their respective significance levels are largely confirmed, it is notable that the spatial parameter ρ is not significant in any case. Presumably, the exclusion of the USA and Brazil poses a significant issue for our work, as both countries are in the midst of their energy transition. Furthermore, as major economies active in international trade, which we use to construct proximity matrices, their exclusion weakens our spatial models, disrupting key connections and reducing the representativeness of our findings. It is also worth noting that CAPMF and EPS are strongly correlated, with a correlation index of 0.843 for the entire panel and 0.897 for the EU sub-panel.

5. Conclusions

Does economic policy uncertainty affect the climate challenge? Empirical evidence is limited and does not support the literature on the broader relationship between EPU and carbon dioxide emissions, which often neglects to focus on the underlying mechanisms.

Our paper employed panel regression models over 15 countries and incorporates additional socio-technical factors, such as climate policy stringency, energy intensity, RD&D expenditures in energy technologies, imports of solar and wind technologies, controlling for national wealth and CO_2 emissions. The analysis showed that elevated levels of EPU not only do not impede REP but, typically associated with a rise in fossil fuel prices, serve as a disincentive for investments in coal and oil, thus promoting renewables, particularly in the EU. Moreover, high EPU correlates with high financial risks and costs, which seem to exist less on renewables, given their less mature stage of development and their expected high-growth rates.

Climate policy has an indirect rather than direct influence on renewable energy production within domestic borders and highlights the critical role of trade and international cooperation in promoting sustainable energy systems. This finding is relevant for collective climate agreements such as the Paris Agreement. Policymakers should use all possible mechanisms to reinforce spillover effects, such as trade agreements, that integrate green standards or emissions targets. In this perspective, the EU Green Deal aims to ensure that EU-wide environmental policies have an external impact, incentivizing partners to adopt similar standards.

In addressing climate change, countries should not only increase their own share of renewables, but also collaborate with economic partners to promote regulatory compliance. This aligns with broader climate goals like the Paris Agreement, the US Inflation Reduction Act (IRA), and the EU Green Deal, which prioritize resilience, clean energy transition, and collective policy targets to support sustainable economic growth globally.

Further results confirmed the positive impact of energy intensity on REP. Given this underlying relationship, governments should set high targets to encourage more sustainable practices. In line with the literature, evidence supports the role of RD&D budgets: governments should prioritize public expenditure on energy technology as a crucial lever of the climate challenge. Imports of solar and wind technologies have a positive impact on REP, with most countries benefiting from external knowledge. Nonetheless, policymakers should not overlook the crucial role of maintaining a domestic green tech manufacturing base. Also, this means encouraging internal knowledge. Overall economic progress, as reflected by GDP, fosters the deployment of renewables, and CO_2 emissions correlates negatively with REP.

Generally, by promoting a stable socio-technical regime, countries can mitigate the volatility associated with traditional fossil fuel markets. In this regard, the US IRA seeks to reduce reliance on imported fossil fuels while stimulating green industry, even in the face of shifting economic landscapes. The socio-technical regime needs to remain resilient, supporting renewables even in times of economic uncertainty. This means that attention to the climate challenge should never waver, and governments should continue or even amplify supportive policies.

Some results need further scrutiny. The introduction of indirect spillovers into the models generated some mixed evidence with regards to EPS, possibly due to time delays, heterogeneity across countries, or a sort of indolence in the domestic energy market. Moreover, spatial regression models have emphasised the influence of latent factors on REP, and additional analyses are requested to investigate the impact of EPS on REP in the presence of spillover effects.

Next steps in research may replicate the analysis for different groups of countries. In this context, the issue of data availability for the EPU variable must be addressed.

Additionally, in this paper, heterogeneity has been accounted for by introducing exogenous spatial regimes, defined based on EU membership. However, data-driven regimes, identified through clustering techniques, or endogenous regimes, where both model coefficients and regime classifications are determined simultaneously, could also be explored (Anselin and Amaral, 2023; Billè et al., 2017; Billè et al., 2018; Postiglione et al., 2013; Postiglione et al., 2010). It is important to note that these works focus exclusively on identifying cross-sectional spatial regimes, without addressing their dynamics over time (i.e., space-time regimes). The adaptation of these methods to panel data remains a topic that requires further exploration in terms of its specific challenges.

Finally, alternative econometric techniques, such as those enabling the specification and estimation of dynamic spatial panel data models, may support and/or enrich the main findings (Elhorst, 2014). These models may simultaneously include a dependent variable lagged in time and/or space, independent variables lagged in time and/or space, serial error autocorrelation, spatial error autocorrelation, spatial-specific and time-specific effects.

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Appendix

The proportion of renewable energy sources in electricity generation within a specific country may be influenced not only by observable determinants, but also by latent elements from trade partners. In this context, these subtle determinants of neighbouring countries manifest themselves as spatial error terms. Consequently, the SEM incorporating spatial error terms has been estimated based on Equation A1:

$$REP_{it} = \beta_0 + \beta_1 EPU_{it-1} + \beta_2 EPS_{it-1} + \beta_3 INT_{it-1} + \beta_4 RDD_{it-1} + \beta_5 IMP_{it-1} + \beta_6 GDP_{it-1} + \beta_7 CO2_{it-1} + u_{it}$$

$$u_{it} = \rho w_{ij} u_{it} + v_{it} \quad \text{(A1)}$$

where u_{it} and v_{it} represent the stochastic errors, with variance and mean equal to 0, and ρ is the spatial lag parameter. The results are highlighted in Table A1, where φ is the random effect.

Table A1. SEM estimation and test results.

Introducing spatial error terms reveals two noteworthy insights. Firstly, the previously considered explanatory variables exhibit a significant impact and anticipated direction on REP (except for INT). Secondly, REP within a specific country is influenced, not only by observable factors such as EPU, EPS, RDD, IMP, GDP and CO2, but also by latent influences originating from interconnected regions (as indicated by the statistically significant ρ value). Thus, the presence of spatial spillovers is confirmed.

Table 1. Variables description.

Variable	Definition	Source
REP	Share of electricity production from renewables	Our World in Data
EPU	Economic Policy Uncertainty Index	EPU website
EPS	Environmental Policy Stringency Index	OECD
INT	Tonnes of oil equivalent per thousand 2005 US dollars of GDP calculated using PPPs	OECD
RDD	Energy technology RD&D budgets (per thousand units of GDP)	IEA
IMP	Import of solar and wind technologies (share of GDP, in thousands of current US dollars)	UN
GDP	GDP per capita (constant 2015 US$)	World Bank
CO2	CO2 emissions (metric tons per capita)	World Bank

Table 2. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
REP	420	25.481	24.075	1.103	95.406
EPU	402	126.448	68.658	37.603	542.766
EPS	405	2.258	1.077	0.167	4.889
INT	420	0.108	0.039	0.028	0.242
RDD	364	0.324	0.204	0.027	0.985
IMP	385	3.163	1.767	0.590	11.404
GDP	417	35709.480	13592.990	6358.686	88966.670
CO2	390	9.450	4.510	1.382	20.470

Table 3. Estimation results of linear panel regression.

Variable	Dependent: REP_{it}	
	FE	RE
EPU_{it-1}	0.012**	0.015**
	(0.005)	(0.005)
EPS_{it-1}	1.018*	1.090*
	(0.509)	(0.558)
INT_{it-1}	83.191*	132.910***
	(37.052)	(35.567)
RDD_{it-1}	4.828**	6.139**
	(1.703)	(1.877)
IMP_{it-1}	1.175***	1.232***
	(0.236)	(0.261)
GDP_{it-1}	0.000***	0.001***
	(0.000)	(0.000)
$CO2_{it-1}$	-4.272***	-4.257***
	(0.277)	(0.290)
Intercept		21.766***
		(6.284)
R-Squared	0.676	0.615
Adj. R-Squared	0.658	0.608
Hausman test	4.380	
B-P	20.983***	

Note: 1. Standard deviations are in parentheses. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively. 3. Breusch–Pagan (B–P) test tests for heteroskedasticity.

Table 4. Global Moran's I-statistic.

Year	REP	EPU	EPS	INT	RDD	IMP	GDP	$CO2$
1994	-0.031	-0.067	-0.032	0.205***	-0.122	-0.156	-0.046	0.148**
2008	-0.053	0.008	-0.079	0.199***	0.035	-0.066	0.017	0.196***
2021	-0.042	-0.153	-0.092	0.128**	-0.044	-0.041	0.025	0.289*

Note: 1. The null hypothesis is the absence of global spatial autocorrelation. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively.

Table 5. Results of spatial dependence diagnostic tests.

Test	Random effect			Fixed effect		
	Statistic	DF	p-value	Statistic	DF	p-value
LM-Error	23.406***	1	0.000	24.234***	1	0.000
LM-Lag	62.812***	1	0.000	64.508***	1	0.000
LM-Error (Robust)	1.126	1	0.289	0.794	1	0.373
LM-Lag (Robust)	40.531***	1	0.000	41.068***	1	0.000

Note: *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively

Table 6. Hausman test results for spatial models.

Test	Random effect		
	Statistic	DF	p-value
Spatial Error	10.799	7	0.148
Spatial Lag	1.212	7	0.991

Note: *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively

Table 7. Comparison of four models based on two different posterior model probabilities.

Models		Uniform *Prior*
	Log marginal	Model probabilities
SLM	-1261.228	0.000
SEM	-1289.024	0.000
SDM	-1250.586	0.173
SDEM	-1249.022	0.827

Models		Beta *Prior*
	Log marginal	Model probabilities
SLM	-1260.896	0.000
SEM	-1288.692	0.000
SDM	-1250.253	0.173
SDEM	-1248.692	0.827

Table 8. SDEM estimation and test results.

Variable	Dependent: REP_t
	Random Effect
EPU_{t-1}	0.001
	(0.005)
EPS_{t-1}	-1.616*
	(0.628)
INT_{t-1}	140.240***
	(36.996)
RDD_{t-1}	13.676***
	(2.158)
IMP_{t-1}	0.796***
	(0.236)
GDP_{t-1}	0.000***
	(0.000)
$CO2_{t-1}$	-3.649***
	(0.289)
$W\ EPU_{t-1}$	-0.001
	(0.012)
$W\ EPS_{t-1}$	-0.896
	(1.434)
$W\ INT_{t-1}$	369.660**
	(124.920)
$W\ RDD_{t-1}$	9.539
	(6.595)
$W\ IMP_{t-1}$	1.116*
	(0.650)
$W\ GDP_{t-1}$	0.002***
	(0.000)
$W\ CO2_{t-1}$	-3.323***
	(0.649)
Intercept	-56.384*
	(27.915)
φ	19.598**
	(7.472)
ρ	0.535***
	(0.079)

Note: 1. Standard deviations are in parentheses. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively.

Table 9. SDEM estimation and test results – EU vs. non-EU countries.

Variable	EU	non-EU
	Dependent: REP_t	Dependent: REP_t
	Random Effect	Random Effect
EPU_{t-1}	0.019***	-0.012
	(0.005)	(0.007)
EPS_{t-1}	-4.916***	-0.994
	(0.687)	(0.820)
INT_{t-1}	229.130***	-116.210*
	(40.028)	(49.121)
RDD_{t-1}	10.625**	3.628
	(3.573)	(2.238)
IMP_{t-1}	0.547**	1.088*
	(0.205)	(0.537)
GDP_{t-1}	0.000***	0.000
	(0.000)	(0.000)
$CO2_{t-1}$	-5.176***	-1.478***
	(0.414)	(0.329)
$W\ EPU_{t-1}$	0.011	0.009
	(0.010)	(0.012)
$W\ EPS_{t-1}$	5.577***	-5.719**
	(1.312)	(1.849)
$W\ INT_{t-1}$	-170.640	113.330
	(142.190)	(146.780)
$W\ RDD_{t-1}$	3.041	8.025
	(6.975)	(6.666)
$W\ IMP_{t-1}$	-0.781	0.551
	(0.502)	(0.956)
$W\ GDP_{t-1}$	0.001	0.001*
	(0.000)	(0.000)
$W\ CO2_{t-1}$	0.514	-1.493*
	(0.889)	(0.674)
Intercept	-23.438	33.601
	(45.293)	(38.091)
φ	36.317**	
	(14.014)	
ρ	0.305*	
	(0.155)	

Note: 1. Standard deviations are in parentheses. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively.

Table 10. SDEM estimation and test results - CAPMF in place of EPS.

Variable	Dependent: REP_t
	Random Effect
EPU_{t-1}	0.006
	(0.005)
$CAPMF_{t-1}$	-0.061
	(0.895)
INT_{t-1}	210.890***
	(34.629)
RDD_{t-1}	4.603**
	(1.917)
IMP_{t-1}	0.756***
	(0.199)
GDP_{t-1}	0.000***
	(0.000)
$CO2_{t-1}$	-3.605***
	(0.305)
$W\ EPU_{t-1}$	-0.004
	(0.008)
$W\ CAPMF_{t-1}$	2.850***
	(1.095)
$W\ INT_{t-1}$	-45.852
	(93.611)
$W\ RDD_{t-1}$	-1.066
	(4.280)
$W\ IMP_{t-1}$	-1.187***
	(0.303)
$W\ GDP_{t-1}$	0.000
	(0.000)
$W\ CO2_{t-1}$	-2.407***
	(0.738)
Intercept	32.773*
	(18.358)
φ	21.334**
	(2.415)
ρ	0.053
	(0.100)

Note: 1. Standard deviations are in parentheses. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively.

Table 11. SDEM estimation and test results – EU vs. non-EU countries. CAPMF in place of EPS.

Variable	EU	non-EU
	Dependent: REP_t	Dependent: REP_t
	Random Effect	Random Effect
EPU_{t-1}	0.016***	-0.009
	(0.005)	(0.009)
$CAPMF_{t-1}$	-1.841*	0.134
	(1.078)	(1.361)
INT_{t-1}	231.080***	81.229
	(39.663)	(61.471)
RDD_{t-1}	6.328*	1.343
	(3.545)	(2.485)
IMP_{t-1}	0.849***	0.548
	(0.198)	(0.587)
GDP_{t-1}	0.000***	0.000
	(0.000)	(0.000)
$CO2_{t-1}$	-4.490***	-1.134**
	(0.444)	(0.535)
$W\ EPU_{t-1}$	-0.020**	0.030**
	(0.009)	(0.014)
$W\ CAPMF_{t-1}$	4.910***	1.372
	(1.405)	(1.834)
$W\ INT_{t-1}$	-129.780	133.530
	(100.640)	(179.070)
$W\ RDD_{t-1}$	-14.532**	-5.378
	(7.218)	(6.207)
$W\ IMP_{t-1}$	-1.029***	-0.623
	(0.319)	(0.704)
$W\ GDP_{t-1}$	0.000	0.001
	(0.000)	(0.001)
$W\ CO2_{t-1}$	-2.128**	-1.979
	(0.835)	(1.560)
Intercept	54.953	-5.337
	(42.847)	(37.473)
φ	24.250**	
	(10.291)	
ρ	-0.080	
	(0.106)	

Note: 1. Standard deviations are in parentheses. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively.

Appendix

Table A1. SEM estimation and test results.

Variable	Dependent: REP_t
	Random Effect
EPU_{t-1}	0.015**
	(0.005)
EPS_{t-1}	1.478**
	(0.535)
INT_{t-1}	59.467
	(39.858)
RDD_{t-1}	3.477*
	(1.898)
IMP_{t-1}	1.217***
	(0.250)
GDP_{t-1}	0.000***
	(0.000)
$CO2_{t-1}$	-3.158***
	(0.279)
Intercept	22.571*
	(8.834)
φ	23.985**
ρ	0.435***
Hausman test	10.799

Note: 1. Standard deviations are in parentheses. 2. *, **, *** denote significance at the 0.1, 0.05, and 0.01 statistical levels, respectively.