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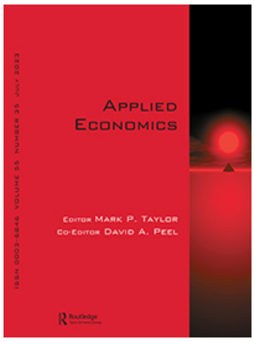

Applied Economics

Routledge
Taylor & Francis Group

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

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To cite this article: Patrick Schembri, Huijie Yan & Katia Radja (2023): Does disaggregated renewable energy stimulate economic growth? The role of spatial effect, Applied Economics, DOI: 10.1080/00036846.2023.2167917

To link to this article: https://doi.org/10.1080/00036846.2023.2167917

Published online: 23 Jan 2023.

APPLIED ECONOMICS
https://doi.org/10.1080/00036846.2023.2167917

Routledge
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Does disaggregated renewable energy stimulate economic growth? The role of spatial effect

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ABSTRACT
This study attempts to empirically investigate the validity of energy-led growth hypothesis for renewable energy sources for developing countries. To this end, this paper estimates the impacts of disaggregated renewable energy sources on economic growth within a multivariate framework including the disaggregated non-renewable energy sources, capital, labour, institutional quality and human capital by using panel data of 32 lower/upper middle income countries over the period 2009 to 2019 and applying spatial dynamic techniques. Our results show the significantly positive impacts of individual renewable sources on economic growth. This study provides the first piece of evidence of spatial spillover effects from renewable energy on economic growth for developing countries. Our analysis reveals the significantly negative impacts of hydroelectricity on economic growth. Our analysis also confirms the importance of labour, institutional quality and human capital in driving economic growth.

KEYWORDS
Renewable energy; growth; spatial effects; developing countries

JEL CLASSIFICATION
O13; O47; O50

I. Introduction

Non-renewable energy has been traditionally considered as a vital driver of economic growth in developing countries (Polat 2021). However, the heavy dependence on fossil energy sources has induced the growing concerns over energy supply security, volatility of energy prices and environmental consequences associated with energy production and consumption (Apergis and Payne 2012). These concerns have forced developing countries to substitute fossil energy sources with renewable energy sources (Jha and Singh 2020). On the one hand, energy transition is considered as a mitigation strategy that developing countries do need to apply in order to respond to the worldwide environmental security challenge expressed through the 2015 Paris agreement on climate change. On the other hand, energy transition is a widely accepted pathway towards sustainable growth for developing countries. As a result, development of renewable energy as a means of mitigating climate change while maintaining economic growth is currently shaping an important policy agenda for developing countries.

Over the past decades, many developing countries have made common effort of increasing investment in renewable energy (Alam et al. 2017). According to the Renewable Global Status Report (2016), the investment in renewables in developing countries increased to USD 156 billion in 2015 from USD 20 billion in 2005. The total investment in renewables in developing countries even began to exceed that in developed countries in 2015.[1]

However, the development of renewable energy implies high investment costs, partly due to the intermittent nature of some renewable energy sources (Marques and Fuinhas 2012). In addition, the observed increase in the share of renewables in current energy mixes does not yet make it possible to compensate for the associated loss in the capacity for producing electricity from fossil fuels (Marques and Fuinhas 2012). Both high investment costs of renewable energy and low fossil energy use may induce a serious drag on economic growth that eliminates the positive influence of renewable energy technological progress on

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[1]The report also revealed that the top ten renewable energy investors consisted of six developing countries and four developed countries in 2015. The six developing countries are Brazil, China, India, Mexico, the Russian Federation and South Africa. The four developed countries include Chile, Germany, Japan and United States.

economic growth. In this setting, the purpose of this study is to investigate whether and to what extent renewable energy sources contribute to economic growth process in the developing countries. Our research seeks to provide rich policy implications for managing environmental and economic conflicts linked to renewable energy sources and for the design of efficient renewable energy policies in the quest for a sustainable energy system.

The energy-led growth hypothesis (i.e. energy consumption contributes to economic growth) has long been a subject of intense debate in the energy-growth literature.[2] However, the empirical outcomes of the existing studies are still until now inconsistent with each other (Emirmahmutoglu et al. 2021).[3] In contrast, the energy-led growth hypothesis for renewable energy sources has only recently been investigated (Apergis and Payne 2012; Menegaki 2011). The effects of renewable energy sources on economic growth have not been fully examined (Inglesi-Lotz 2016). Hence, there is still a long way to go before achieving conclusive results as to the validity of the energy-led growth hypothesis for renewable energy sources. In addition, most of the earlier studies focus on developed countries due to the availability and reliability of data, while with limited emphasis on developing countries, even though the investment in renewable energy in developing economies mushroomed over the near past. Therefore, additional research explaining the impact of renewable energy on economic growth of developing countries is warranted. In this context, this study contributes to the scant literature on the topic in three different aspects.

Firstly, this paper focuses on exploring the impacts of disaggregate renewable energy sources on the economic growth of developing countries. This kind of studies is essential given the important policy implications, that is, the policy makers are suggested to formulate different strategies for each renewable energy source in order to achieve sustainable economic growth (Dogan 2016).[4] Moreover, the use of disaggregate renewable energy data allows for capturing the extent to which different countries depend on different energy resources. However, the studies identifying the effects of disaggregate renewable energy sources on economic growth are very scarce (Ohler and Fetters 2014).[5] Therefore, a further study on the impacts of disaggregate renewable energy in the developing countries is still necessary.

Second, this paper adds to the scant literature by considering simultaneously the disaggregated renewable and non-renewable energy sources. This consideration allows us to identify the dissimilar effects of energy sources in enhancing the economic growth prospects of developing countries and analyse the substitutability between renewable and non-renewable energy sources (Apergis and Payne 2012). The previous studies have largely omitted to include the disaggregated non-renewable energy alongside renewable energy, although this omission may lead to the wrong conclusions and inconsistent results about the renewable energy-growth nexus (Apergis and Payne 2012; Marques and Fuinhas 2012).[6]

Finally, this is the first piece of empirical cross-sectional analyses considering the role of spatial spillover effects for developing countries. The innovation on the model specification in the renewable energy-growth literature is necessary in order to avoid increasing the number of conflicting results and making the policymaking more uncertain (Apergis and Tang 2013; Karanfil 2009; Ozturk 2010). It has been recognized that the economic growth of one country depends on the growth and economic conditions of nearby countries (Basile

[2]The energy-growth literature focuses on testing four hypotheses: the growth hypothesis (unidirectional causality from energy to economic growth); the conservation hypothesis (unidirectional causality from economic growth to energy); the feedback hypothesis (bidirectional causality between energy and economic growth); the neutrality hypothesis (no causality between energy and economic growth). See Apergis and Payne (2012) and Tugcu, Ozturk, and Aslan (2012) for a discussion in detail.

[3]The differences in sample periods, econometric methodologies and countries' characteristics are considered as the main reasons of the rather conflicting results (Ozturk 2010; Tugcu, Ozturk, and Aslan 2012).

[4]In contrary, the results from the analysis of aggregate renewable energy cannot be generalized to disaggregate renewable energy and thus the policy suggestions based on this kind of studies are hard to implement (Fang and Chen 2017).

[5]To our knowledge, only the following two studies have provided disaggregated analyses for developed countries. Ohler and Fetters (2014) have provided empirical evidence by examining the causal relationship between individual renewable sources (including biomass, geothermal, hydroelectric, solar, waste, and wind) and economic growth using data from 20 OECD countries for the period 1990–2008. Armeanu, Vintila, and Gherghina (2017) have analysed the influence of disaggregate renewable energy (including biomass, hydropower, geothermal, wind and solar) on the economic growth of European Union (EU)-28 countries for the period of 2003–2014. These two studies highlight the importance of this new avenue of research.

[6]Among the studies reviewed, only one study, Long et al. (2015), differentiated between disaggregated renewable and non-renewable energy sources.

2008). The spatial spillovers as a major engine of technological progress result from international trade, foreign direct investment, technology transfers and human capital externalities (Ertur and Koch 2007; Radmehr, Henneberry, and Shayanmehr 2021). Another spatial effect arises from the fact that energy consumption pattern in one region could influence energy consumption in neighbouring regions and therefore, affects economic growth of its neighbours (Fotis, Karkalakos, and Asteriou 2017). As a consequence, estimation procedures omitting the spatial effects may cause model misspecification problem, bias the estimated results and hence produce misleading conclusions about policy inferences (Anselin 1988; LeSage and Pace 2009). Nevertheless, the idea of spatial spillover effects has been fully neglected by the existing literature on the topic focusing on developing countries.[7]

The paper is organized as follows. Section II describes the empirical analysis. Section III discusses the main results, and Section IV offers concluding remarks and policy recommendations.

II. Methods

Empirical model and data

Empirical model

To investigate the impacts of renewable energy sources on economic growth, this study applies the following production function:

$$Y_{it} = f(K_{it}, L_{it}, RE_{it}, TE_{it}, X_{it}) \tag{1}$$

Where, Y denotes aggregate output, K represents capital stock, L stands for labour, RE and TE are respectively renewable and traditional energy sources, X denotes a vector of other control variables that consist of institutional quality and human capital, which potentially influence economic growth. The subscript i denotes country and t denotes year. In this function, capital, labour and energy are treated as separate inputs. Capital, labour, institutional quality and human capital are included in the model in order to avoid omission bias problem (Adekoya et al. 2022; Ohler and Fetters 2014).[8] The production function defined as Equation. (1) is extended to analyse the impacts of disaggregated energy sources on economic growth by replacing RE and TE with each individual renewable and traditional energy sources.

Using log-linearization, Equation. (1) could be rewritten as:

$$\begin{aligned} lnY_{it} = {} & \beta_0 + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 lnRE_{it} \\ & + \beta_4 lnTE_{it} + \beta_5 lnINST_{it} + \beta_6 lnHC_{it} + \delta_i \\ & + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Where β_0 is the intercept, β_1, β_2, β_3 β_4,β_5 and β_6 are the coefficients which measures the output elasticities with respect to capital stock, labour, disaggregated renewable and traditional energy sources, institutional quality and human capital respectively, δ_i refers to individual fixed effect (regional dummies)[9], δ_t correspond to time fixed effect (time trend)[10], and ε_{it} is error term.

Data

The multivariate framework encompasses real GDP per capita (Y) in constant 2015 US \$, real gross fixed capital formation per capita (K) in constant 2015 US \$,

[7]To our knowledge, only the following three studies have made important contributions by capturing the idea of spatial effects. Chica-Olmo, Sari-Hassoun, and Moya-Fernández (2020) investigated the spatial dependence between GDP and aggregated renewable energy consumption by using a spatial Durbin model with two-way fixed effects and focusing on 26 European countries over the period 1991–2015. Radmehr, Henneberry, and Shayanmehr (2021) explored the relationships among economic growth, aggregated renewable energy consumption and carbon emissions by applying spatial simultaneous equations models with a generalized spatial two-stage least squares method and analysing panel data from 21 European countries over the period 1995–2014. Cui, Weng, and Song (2022) investigated the spatial effects of both aggregated renewable energy consumption and financial inclusion on economic growth by employing a spatial Durbin model with fixed effects and using panel data from 40 countries for the period 2010–2020.

[8]Literature concerning economic growth has indicated that physical capital and labour are the conventional factors of economic production (see Arbex and Perobelli 2010). Numerous studies have documented the important role of institutional quality and human capital in economic growth (see Fang and Chen 2017; Zallé 2019). Therefore, we incorporate capital, labour, institutional quality and human capital into the production process.

[9]The individual fixed effect is included in the model to control for time-invariant regional characteristics, which may affect both economic growth and renewable energy supply, such as resource endowment and climate conditions. The inclusion of individual fixed effect enables us to yield causal inference. We thank an anonymous reviewer for pointing out this issue. Regional dummies distinguish regions to which countries belong. All the countries in the sample are divided into Asian, African, European and American regions.

[10]The time fixed effect is incorporated into the model to account for time-dependent macro factors that may influence both economic performance and renewable energy supply capacity, such as, financial crises, external energy demand shocks, and changes over time in global energy prices. We use a linear time trend to control for time-specific factors.

labour force per capita (*L*).[11] These data are obtained from the World Bank's World Development Indicators. Electricity production from biomass & waste (*BIOM*), or wind (*WIND*) measured in billions of kilowatt-hours as a proxy for disaggregated renewable energy source (*RE*). Disaggregated traditional energy source *TE* is defined as coal supply (*COAL*) or oil supply (*OIL*)[12] measured in million tonnes of oil equivalent[13] or hydroelectric generation (*HYDR*) measured in billions of kilowatt-hours.[14] The data on *BIOM, WIND* and *HYDR* are drawn from the U.S. Energy Information Administration. The data on *COAL* and *OIL* are collected from the International Energy Agency.[15] Following Zhang and Kim (2022), the institutional quality (*INST*) is measured by the arithmetic mean of all six dimensions of the World Bank's Worldwide Governance Indicators, which include voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption.[16] Aggregating all the dimensions of governance into a single index helps to capture the joint impact of institutional quality. To capture variations in human capital across countries and time, we use the human capital index taken from the Penn World Table version 10.0 database.[17] Table 1 shows the definition of variables and data sources.

After identifying the variables used in this study, we collect their data. The selection of the countries and sample period are based on the availability of annual data, spanning the period 2009 to 2019.[18] Our sample is restricted to both lower and upper middle income countries based on the World Bank's classification for the year 2019.[19] Out of the 106 countries categorized as lower/upper middle income, only 43 countries have data on the variables *BIOM* and *WIND* either for the entire period under analysis or for some years of the sample period.[20] During the data collection process, we find that there is no data available on some variables of interest in the case of 10 countries.[21] Thus, this leaves us with a sample of 32 countries.[22] These countries are major global renewable electricity producers, collectively accounting for over half of global renewable electricity production since 2017.[23]

After collecting their data, we implement the interpolation method to fill in the missing values of variables *BIOM, WIND* and *COAL* so as to obtain a balanced panel dataset.[24] The missing values prevent us from running the spatial panel model because spatial econometrics need balanced panel data in order to take into account the spatial dependence at each point of time (Sanso-Navarro, Vera-Cabello, and Puente-

[11]We divide the capital and labour variables by total population (extracted from World Development Indicators) to calculate the fixed capital per capita and labour force per capita.

[12]We could not include natural gas production in our analyses because of the large missing information in both the U.S. Energy Information Administration and the International Energy Agency datasets which severely restricts the number of countries available for analysis.

[13]We use 2022 conversion factors to convert coal supply and oil supply measured in terajoule into million tonnes of oil equivalent.

[14]We consider hydropower as a traditional energy source for two reasons. First, the development of hydropower unavoidably results in environmental risks, such as, forest ecosystem degradation and water quality deterioration. Second, hydropower has been a technically well-established energy source and has served as the foundation energy source for many countries. Thus, hydropower hardly reflects the advanced development of energy resources. We thank an anonymous reviewer for pointing out these issues.

[15]The U.S. Energy Information Administration database also contain data on coal production and petroleum and other liquids production. However, these data are largely unavailable for many countries (especially for developing countries) under our studied period. Thus the International Energy Agency database is preferred.

[16]We use percentile rank in order to avoid the possibility of negative or zero scores in the logarithm. The percentile rank ranging from 0 corresponding to lowest rank to 100 being the highest.

[17]Human capital index has been widely used in previous studies (see, e.g. Yao et al. (2019)).

[18]We choose 2009 as the starting period because the data on the variables *BIOM* and *WIND* are largely unavailable for the earlier period. We select 2019 as the ending year since the data on the variables *COAL* and *OIL* are available only until this year for most countries.

[19]Both lower and upper middle income countries are included in the sample in order to increase the sample size and better fulfil the requirements of the estimation method used in the next subsection. We do not consider low income countries in our analysis because the data for the variable *WIND* is missing for almost all the low income countries spanning 11 years (2009–2019).

[20]We allow countries with a maximum of six missing observations for each variable (*BIOM* and *WIND*), in whose case we interpolate the data. So the countries with gaps in excess of 6 years are excluded from the sample, like Bosnia and Herzegovina, and Lebanon.

[21]Concretely, the countries Azerbaijan, Ecuador, Fiji, Guyana, Moldova and Vanuatu are excluded from the sample due to the lack of data on coal supply over the entire studied period. In addition, Bulgaria, Cuba, Philippines and South Africa are excluded from the analysis for the missing human capital data.

[22]Cambodia is also not included in our sample, because the exact same values for the variable *WIND* are reported for all the 11 years under analysis. In detail, this study covers Argentina, Bangladesh, Belarus, Bolivia, Brazil, China, Colombia, Costa Rica, Dominican Republic, Egypt, Guatemala, Honduras, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kenya, Mexico, Morocco, Nigeria, North Macedonia, Pakistan, Peru, Russian Federation, Serbia, Sri Lanka, Thailand, Turkey, Ukraine and Vietnam. Among these countries, 11 countries are located in Asia, 4 countries are located in Africa, 6 countries are located in Europe, and 11 countries are located in America. Thus, our sample covers countries with different geographical proximity.

[23]Authors' own calculation based on data from U.S. Energy Information Administration. In detail, our sample of 32 countries collectively accounts for 44.5%, 46%, 45.4%, 46.8%, 46.9%, 48%, 48.5%, 49.5%, 50.1%, 51.1%, and 52.2% of global renewable electricity production in 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018 and 2019, respectively.

[24]The missing information rates of the variables *BIOM, WIND* and *COAL* are 6.25%, 6.82% and 1.99%, respectively.

Table 1. Definition of variables and data sources.

Variable	Definition	Data source
Y	Real GDP per capita in constant 2015 US $	World Development Indicators
K	Real gross fixed capital formation per capita in constant 2015 US $	World Development Indicators
L	Labour force per capita	World Development Indicators
BIOM	Electricity production from biomass & waste measured in billions of kilowatt-hours	U.S. Energy Information Administration
WIND	Electricity production from wind measured in billions of kilowatt-hours	U.S. Energy Information Administration
HYDR	Hydroelectric generation measured in billions of kilowatt-hours	U.S. Energy Information Administration
COAL	Total coal supply measured in million tonnes of oil equivalent	International Energy Agency
OIL	Total oil supply measured in million tonnes of oil equivalent	International Energy Agency
INST	Average of six institutional indices in form of percentile ranks including voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption	Worldwide Governance Indicators
HC	Human capital index, based on years of schooling and returns to education	Penn World Table 10.0

Ajovín 2020).[25] In the end, our final balanced panel dataset covers 32 countries over the 11-year period from 2009 to 2019, resulting in 352 observations.

The descriptive statistics for all the variables across the sample after the interpolation process are shown in Table 2.[26] The correlation coefficients between disaggregated renewable energy sources and economic growth for all countries are reported in Table 3. This table suggests that *BIOM*/*WIND* and *Y* are highly positively and significantly correlated with each other in the majority countries.[27] These results indicate that renewable energy sources play an important role in promoting economic activities across most countries.

Table 2. Descriptive statistics.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Y	5320.1	3264.7	931.99	14200	352
K	122032	80113	15597	434881	352
L	0.4394	0.0857	0.2435	0.5942	352
BIOM	4.918	14.71	0.001	121.1	352
WIND	8.598	39.46	0.001	406	352
HYDR	64.11	182.3	0.023	1254	352
COAL	82.87	341.3	0.0002	2071	352
OIL	48.19	96.6	0.8911	647.9	352
INST	38.11	12.26	14.69	72.67	352
HC	2.525	0.6577	1.162	3.613	352

Estimation methods

Spatial dynamic panel model

We employ spatial dynamic panel models in order to simultaneously accommodate dynamic adjustments and spatial dependence and thus produce more accurate and reliable estimation results (Hao and Peng 2017).

Equation. (2) could be extended to include spatial interaction effects by specifying the following two spatial dynamic panel models:

$$lnY_{it} = \tau lnY_{it-1} + \rho \sum_{j=1}^{n} w_{ij} lnY_{it} + \gamma x_{it} + \sigma_i + \sigma_t + \varphi_{it} \quad (3)$$

and

$$lnY_{it} = \tau lnY_{it-1} + \rho \sum_{j=1}^{n} w_{ij} lnY_{it} + \gamma x_{it} + \pi \sum_{j=1}^{n} w_{ij} x_{it} + \sigma_i + \sigma_t + v_{it} \quad (4)$$

Where Y_{it-1} is the real GDP per capita in country i at year t-1, x_{it} is an matrix of explanatory variables, w_{ij} is an element of the spatial weights matrix, ρ is the spatial autoregressive coefficient, γ represents coefficients of the explanatory variables,π is spatial coefficient of the explanatory variables, σ_i is the individual effect, σ_t corresponds to time fixed effect, φ_{it} and v_{it} are the independent and identically distributed random error term, τ represents beta convergence parameter.[28]

Before estimating the spatial dynamic econometric models, spatial weight matrix which captures the spatial dependence structure across countries in our sample needs to be defined. In earlier studies of spatial econometrics, the spatial weight matrix was most commonly specified to

[25]Therefore, we capitalize on the available data and interpolate the missing values by assuming a linear relation and using an inverse distance weight with the available value that is the nearest having the largest weight (Castañeda Rodríguez 2018). The missing values are estimated through interpolation with the help of the Stata command *mipolate*.

[26]We further compute coefficient of variation that is defined as the ratio of standard deviation to mean and used to measure the relative dispersion of the variables. In detail, the coefficient of variation for *WIND*, *COAL*, *BIOM*, *HYDR*, *OIL*, *K*, *INST*, *HC* and *L* are 4.589, 4.118, 2.991, 2.844, 2.005, 0.656, 0.322, 0.26 and 0.195. Thus, *WIND* is the most volatile explanatory variable, followed in order by *COAL*, *BIOM*, *HYDR*, *OIL*, *K*, *INST*, *HC* and *L*.

[27]For example, the highest correlation value between *BIOM* and *Y* is found in China (0.9919), followed by Turkey (0.9589) and Mexico (0.9526). The highest correlation value between *WIND* and *Y* is found in Turkey (0.9936), followed by China (0.9912) and India (0.9840).

[28]If τ is statistically significant and inferior to 1, the beta convergence of real GDP per capita is confirmed.

Table 3. Correlation between renewable energy and economic growth.

	Countries	Correlation	Countries	Correlation	Countries	Correlation
Biomass & waste	Argentina	−0.4751	Honduras	0.7747***	North Macedonia	0.3407
	Bangladesh	0.9080***	India	0.9337***	Pakistan	0.4794
	Belarus	0.8148***	Indonesia	0.9357***	Peru	−0.0096
	Bolivia	0.7493***	Iran	0.1221	Russian Federation	0.2876
	Brazil	0.1518	Jamaica	−0.5461*	Serbia	0.8259***
	China	0.9919***	Jordan	0.9031***	Sri Lanka	0.8252***
	Colombia	0.9188***	Kazakhstan	0.1373	Thailand	0.9452***
	Costa Rica	0.7279***	Kenya	−0.7522***	Turkey	0.9589***
	Dominican Republic	0.8565***	Mexico	0.9526***	Ukraine	0.0512
	Egypt	−0.7680***	Morocco	0.6645**	Vietnam	0.8668***
	Guatemala	0.9326***	Nigeria	0.6455**		
Wind	Argentina	−0.0325	Honduras	0.8468***	North Macedonia	0.3131
	Bangladesh	0.9127***	India	0.9840***	Pakistan	0.8686***
	Belarus	0.6016**	Indonesia	0.6273**	Peru	0.8380***
	Bolivia	0.4342	Iran	−0.3338	Russian Federation	0.6200**
	Brazil	−0.0898	Jamaica	0.6127**	Serbia	0.3886
	China	0.9912***	Jordan	−0.7475***	Sri Lanka	0.8849***
	Colombia	−0.1503	Kazakhstan	0.8764***	Thailand	0.9416***
	Costa Rica	0.9767***	Kenya	0.8484***	Turkey	0.9936***
	Dominican Republic	0.7967***	Mexico	0.9833***	Ukraine	−0.0586
	Egypt	0.9656***	Morocco	0.9797***	Vietnam	0.9425***
	Guatemala	0.2985	Nigeria	0.5605*		

***, ** and * denote a significance of 1%, 5% and 10%, respectively.

measure geographic proximity. The merit of geographical matrix is that it is indeed strictly exogenous (Arbia, Battisti, and Di Vaio 2010). Recently, economic proximity has been introduced to capture neighbourhood between spatial units. The matrix based on economic attributes could measure the distance beyond the geographical notion that still play an important role in shaping the economic relationships across countries (Anselin 2002; Arbia, Battisti, and Di Vaio 2010).

Recent literature has argued that international trade often serves as channels for economic transmission across countries and countries are 'economically closer' if they conduct a large volume trade with each other (Wang, Wong, and Granato 2015). Thus, in line with Nan et al. (2022), our spatial analysis applies a spatial weight matrix that depends on intensity of bilateral trade flows so as to capture the economic interdependency among countries.[29] The trade-intensity-based spatial weight matrix $W(k)$ is defined as follows:[30]

$$W(k) = \begin{cases} w^*_{ij}(k) = 0 \text{ if } i = j \\ w^*_{ij}(k) = TR_{ij} / \sum_{i \neq j} TR_{ij} \text{ otherwise} \end{cases} \quad (5)$$

Where w^*_{ij} is an element of unstandardized weight matrix W, and TR_{ij} represents total bilateral trade flows (import plus export) between country i and country j. Note that TR_{ij} is the average bilateral trade between country i and country j over the 2009–2019 period.[31] This weight matrix is standardized such that the elements of a row sum up to one (i.e. row standardization).[32]

To check the robustness of the estimation results, we use a first-order queen contiguity weight matrix as an alternative form of the spatial weights matrix.[33] The first-order queen contiguity weight matrix is binary and its element w^*_{ij}takes value 1 if country i and country j share a common geographic border or vertex, and w^*_{ij} has a value of 0 otherwise. All elements of this matrix are also standardized before use.

[29]Larger value of intensity of bilateral trade flows between two countries implies higher dependence between the countries.
[30]The choice of a spatial weight matrix is relatively subjective as it is not guided by economic theory (Hao and Peng 2017; Marbuah and Amuakwa-Mensah 2017).
[31]To avoid the possible endogeneity problem, we follow Ertur and Koch (2011) by calculating the average bilateral trade over the 2009–2019 period. Data on trade flows for each country are taken from the UN Comtrade Database.
[32]Row standardization allows us to interpret the spatial spillover effects as an average of all neighbours (You and Lv 2018).
[33]The queen continuity criterion is one of the most popular criteria for creating geographic weight matrix in the existing literature (see e.g. Cho, Chen, and Poudyal 2010; Leiva, Vasquez-Lavín, and Oliva 2020, among many others).

Estimation issue

System Generalized Method of Moments (GMM) estimator is applied to estimate Equation. (3) and Equation. (4) for several reasons.[34] First, the system GMM estimator corrects for not only the endogeneity of the lagged dependent variable and the spatially lagged dependent variable but also the potential endogeneity of other explanatory variables.[35] Thus, given the potential reverse causality between the explained and the explanatory variables, the system GMM estimator may yield consistent estimates of the desired causal effect.[36]

Second, the system GMM estimator controls for unobservable heterogeneity specific to countries which may affect both the dependent variable and the explanatory variables and thus ensure the reliability of our causal estimates (Nkoa and Song 2020). Third, the system GMM estimator performs better than the difference GMM estimator (Berk, Kasman, and Kılınç 2020).[37] To overcome the drawbacks of the difference GMM approach, the system GMM approach estimates a system of two equations simultaneously: an equation in levels with lagged first differences as instruments, and an equation in first differences with lagged levels as instruments (Zheng et al. 2013).[38] Fourth, the system GMM estimator is appropriate for short panel data (Roodman 2009).[39] Finally, the system GMM estimator has been a popular estimation method for spatial dynamic panel models in the recent studies.[40]

Henceforth, accounting for the aforementioned problems, we use the two-step system GMM estimator to estimate the models in the present paper.[41] $lnY_{-1,}$ $W{*}lnY$, $lnBIOM$, $lnWIND$, $lnHYDR$, $lnCOAL$, $lnOIL$, lnK, lnL, $lnINST$, $W{*}lnBIOM$ and $W{*}lnWIND$ are treated as endogenous in the estimation of Equation. (3) and Equation. (4). $lnHC$ is considered as the predetermined variable in the estimation of the two equations. The first and above lags of the predetermined variable and the second and above lags of the endogenous variable are used for GMM-type instruments.[42] Regional dummies and time trend are treated as exogenous, and they are instrumented in a IV style.

The consistency of the system GMM estimator depends on whether lagged values of the explanatory variables are valid instruments (Ogunniyi et al. 2020). To address this issue, three specification

[34]The system GMM estimator is suggested by Arellano and Bover (1995) and Blundell and Bond (1998).

[35]Spatial panel literature widely uses maximum likelihood estimator. However, this estimator would produce inconsistent and biased estimates if the potential endogeneity of other explanatory variables is present (Zheng et al. 2013).

[36]In this study, endogeneity arising from the reverse causality between renewable energy sources and economic growth may be a serious problem in our model. We are grateful to an anonymous referee for the advice to tackle the problem of reverse causality in our empirical models. One can imagine that, for instance, the worldwide economic crisis may decrease dramatically the investment in renewable energy sources (Li et al. 2021). The presence of endogeneity in our model could also potentially be explained by the reverse causality from traditional energy sources to economic growth. This reverse causality hypothesis touches the energy-growth literature, which provides evidence on the causality running from economic growth to energy use (see Acheampong et al. 2021). Another important concern of endogeneity in our model related to the potential feedback effects from economic growth to institutional quality. That is because the existing literature suggests that economic growth causes improvement in institutional quality (Law, Lim, and Ismail 2013).

[37]The difference GMM estimator is proposed by Arellano and Bond (1991). In the difference GMM approach, the strategy is to remove the individual fixed effect by proceeding with the first difference of level equation and then use lagged variables as the instruments of endogenous variables in the difference equation (Trotta, Hansen, and Sommer 2022; Zheng et al. 2013). The difference GMM estimator suffers from the weak instrument problem which can result in large finite-sample bias and poor precision (Ogunniyi et al. 2020; Trotta, Hansen, and Sommer 2022). Weak instrument problem means that lagged levels of the dependent variable are weak instruments for first differences (Ogunniyi et al. 2020; Trotta, Hansen, and Sommer 2022).

[38]This allows the introduction of more instruments and thus can dramatically improve estimation efficiency (Roodman 2009; Trotta, Hansen, and Sommer 2022).

[39]The short panel data means large cross-sectional dimension with short time dimension, as in our case ($N = 32$; $N = 11$).

[40]See e.g. Espoir and Sunge (2021) and Zheng et al. (2013), among many others.

[41]The system GMM method can be divided into one-step and the two-step estimation methods in accordance with different choices of the weight matrix. The one-step estimator assumes that the error terms are homoscedastic across groups and over time. The two-step estimator uses the estimated residuals from the one-step estimator to construct more efficient heteroskedasticity consistent GMM weighting matrix (Davidson and MacKinnon 2004). In addition, the two-step estimation has been proven to be more efficient than the one-step estimation.

[42]The two techniques suggested by Roodman's (2009) are further used together to address the problem of 'too many instruments'. This problem means that a high instrument count can over fit endogenous variables and weaken the power of the Hansen test to detect invalidity of the system GMM instruments (Roodman 2009). On the one hand, we use only certain lags instead of all available lags for instruments (limiting lags) and combine instruments by adding them into smaller sets (collapsing instruments). On the other hand, conforming to Roodman's (2009) rule of thumb, we keep the number of instruments never larger than the number of individual units in the panel. The regressions are run using Stata command *xtabond2*.

tests, including Hansen over-identification test, Arellano-Bond error autocorrelation test and difference-in-Hansen test, are necessary.[43]

III. Empirical results

Spatial autocorrelation test

To explore the existence of spatial autocorrelation in real GDP per capita, we adopt the global Moran's I index which has been widely used in the literature on spatial studies. The global Moran's I index describes the extent of the overall spatial relationship across all spatial units. The values of global Moran's I index range over [−1,1].[44] A positive value of Moran's I index indicates spatial clustering across the sample countries, with a higher value implying a stronger association (i.e. more positively correlated). By contrast, a negative value denotes spatial dispersion across the sample countries, with a lower value implying a stronger association (i.e. more negatively correlated). A zero value indicates a random distribution of real GDP per capita across countries.

The values of Moran's I index and the associated P-value for real GDP per capita over the period 2009–2019 by using the trade-intensity-based spatial weight matrix are presented in Table 4. As shown, the Moran's I values for real GDP per capita were positive and statistically significant at the 5% and 10% significance levels for the entire time period, suggesting that real GDP per capita were not randomly distributed but rather exhibited a positive spatial interdependence. It implies that the countries with high real GDP per capita (resp. low) are localized close to other countries with high real GDP per capita (resp. low). Hence, the existence of spatial autocorrelation provides a support for necessity of considering spatial effects in the econometric estimation.

Table 4. Global Moran's I index of GDP per capita using trade-intensity-based spatial weight matrix.

Year	Moran's I	Year	Moran's I
2009	0.11***	2015	0.078**
2010	0.106**	2016	0.071**
2011	0.104**	2017	0.064*
2012	0.1**	2018	0.061*
2013	0.097**	2019	0.059*
2014	0.093**		

***, ** and * denote a significance of 1%, 5% and 10%, respectively. The null hypothesis is no global spatial autocorrelation.

To further describe the heterogeneity of spatial association cross different geographic units within the areas under investigation, we construct Moran scatter plot (Marbuah and Amuakwa-Mensah 2017).[45] Using the cross-sectional data of 2010 and 2018, we draw Moran scatter plot to visualize the atypical spatial associations in the data of economic output (see Figure 1). It reveals that in 2010 and 2018 most countries were located in the first and third quadrants, which implies that real GDP per capita displays an obvious positive correlation in spatial distribution. More specifically, the plots show that in 2010 and 2018, 21 countries (66%) and 20 countries (63%) were located in the first and third quadrants.[46] Therefore, the graphical evidence shows the presence of spatial heterogeneity and therefore implies the necessity to consider spatial effects in our empirical analysis.

[43]The Hansen over-identification test examines the overall validity of the instruments by employing the null hypothesis that all instruments as a group are exogenous. The acceptance of this hypothesis means that the instruments are not correlated with the error term (i.e. the instruments are valid). The Arellano-Bond error autocorrelation test is performed under the null hypothesis of no first- or second-order serial correlation in the first-differenced error term. The assumption of no first-order serial correlation should be rejected, whereas the hypothesis of no second-order serial correlation should be accepted. The difference-in-Hansen test investigates the validity of instrument subsets by employing the null hypothesis of exogeneity of the set of examined instruments. Failure to reject the null hypothesis implies that the instruments are exogenous.

[44]The global Moran's I index can be expressed as: $I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2}$ Where n is the number of spatial units (i.e. countries). x_i and x_j represent real GDP per capita of country i and j, respectively. $\bar{x}$ is the mean value of real GDP per capita, i.e. $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$. W_{ij} is an element of the spatial weight matrix.

[45]The Moran scatter diagram plots the spatial lag of variable (Wz) against the original value (z). The values are distributed into four quadrants which correspond to the four types of local spatial association between a region and its neighbours. The first quadrant (upper-right), which depicts a region with a high value is surrounded by neighbours with high values, representing a positive spatial autocorrelation (High-High, HH). The second quadrant (upper-left), which represents a low-value region is surrounded by high-value regions, indicating a negative spatial autocorrelation (Low-High, LH). The third quadrant (lower-left), represents a low-value region is surrounded by low-value regions, meaning a positive spatial autocorrelation (Low-Low, LL). The fourth quadrant (lower-right), represents a high-value region is surrounded by low-value regions, denoting a negative spatial autocorrelation (High-Low, HL).

[46]As an illustration in 2010, Belarus and Argentina were located in the first quadrant (i.e. High-High clustering), meaning that countries with high real GDP per capita surrounded by other countries with high real GDP per capita. Kenya and Sri Lanka were found in the third quadrant (i.e. Low-Low clustering), implying that countries with low real GDP per capita surrounded by other countries with low real GDP per capita.

Panel unit root and cointegration tests

We perform the panel unit root tests and cointegration tests before estimating the empirical models described in the previous section in order to avoid spurious regression problem. To check the stationarity of the variables, HT (Harris and Tzavalis 1999) and CIPS (Pesaran 2007) unit root tests are used in this study.[47] The CIPS test which produces accurate results in the presence of cross-sectional dependence is preferred because Pesaran's (2004) cross-section dependence (CD) tests show that each series exhibits cross-sectional dependence (see Table 5). Results for all the unit root tests are reported in Table 6. As shown, all the variables become stationary after first differencing. Then the integration of all the variables is of order 1, i.e. I(1).

The unique order of integration of these variables leads us to further test the existence of cointegration between them. In doing so, we perform the panel cointegration tests using the Kao cointegration test (Kao 1999).[48] The panel cointegration test results are presented in Table 7. We find that the null hypothesis of no cointegration is rejected at either 1%, 5% or 10% significance levels for all five test statistics under the Model A (Biomass & waste) and Model B (Wind). Equally, four out of the five statistics suggest the rejection of the null hypothesis of no cointegrating relationships under the Model C (Biomass & waste and Wind). To sum up, we could conclude the existence of a long-run cointegration relationship among the variables used in this paper. The evidence of unit root tests and cointegration tests support that the empirical analysis discussed in the next subsection is free from spurious regression problem.

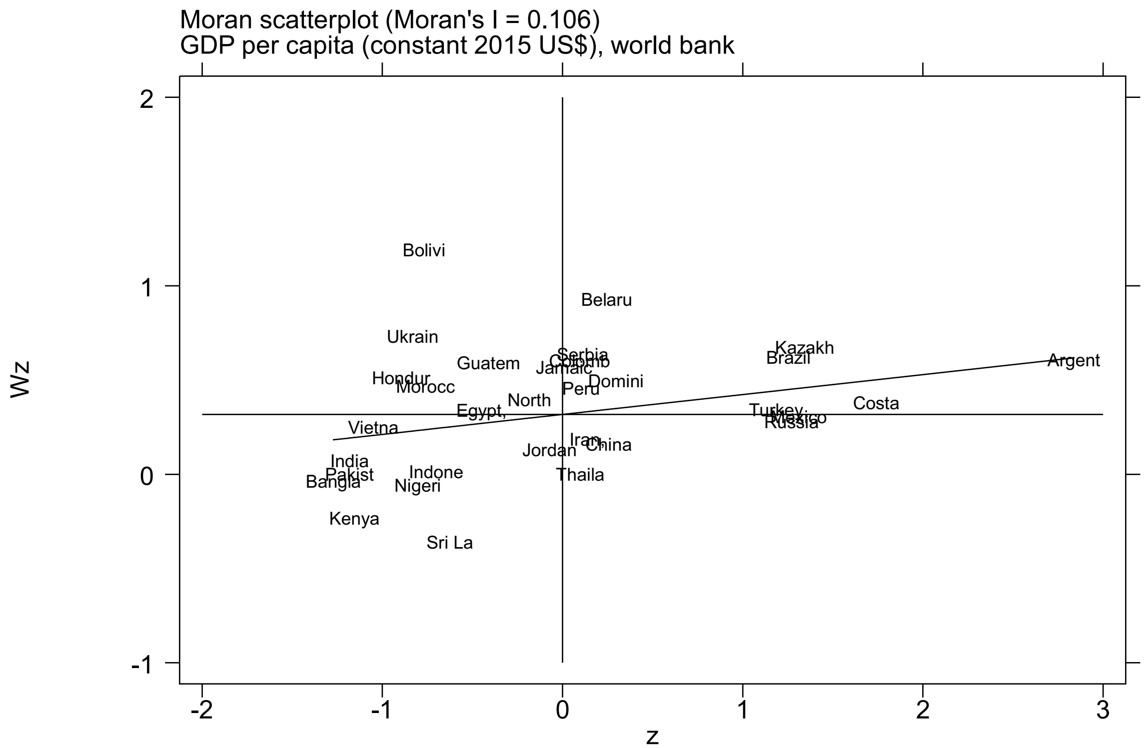
Spatial dynamic regression results

Table 8 presents the estimated results of the spatial dynamic system GMM panel models. The diagnostic statistics reported in the Table 8 show that our spatial dynamic system GMM estimates meet all specification tests, indicating that our estimates are effective and consistent. As expected, the first-order autocorrelation (AR(1)) is present and the second-order autocorrelation (AR(2)) is absent. Hansen tests fail to reject the null hypothesis of jointly valid instruments for all estimated models, indicating that all the instrumental variables used in this study are effective. At the same time, difference-in-Hansen tests fail to reject the null hypothesis of exogeneity of the set of examined instruments, confirming that the instruments are reasonable and effective. In addition, in accordance with Roodman's (2009) rule of thumb, the number of instruments is not larger than that of countries in all of the estimated models.

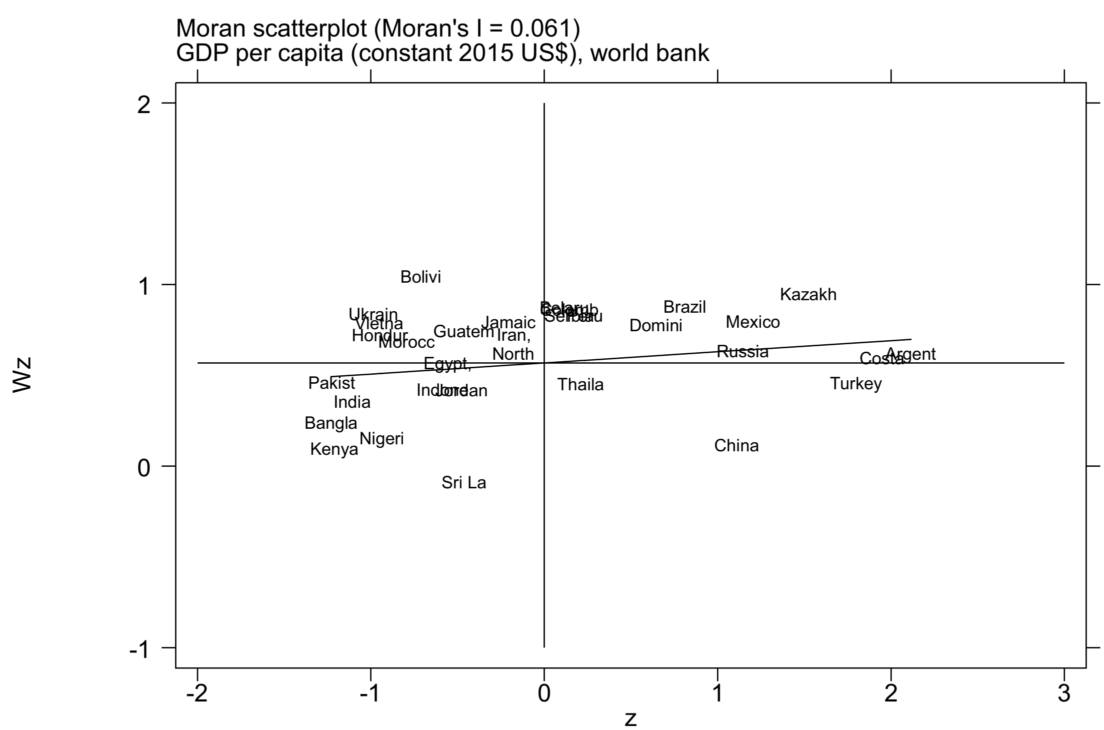
Turning to the coefficient estimates, the estimated coefficient on the lagged dependent variable (lnY_{-1}) is positive and statistically significant at the 1% level in each model, implying that GDP per capita has a path-dependence effect. This evidence corroborates the necessity of using the dynamic panel model.[49] Moreover, the estimated coefficients of lnY_{-1} are inferior to 1 across all the specifications, indicating that there is conditional beta convergence in GDP per capita across countries when spatial effect is accounted for. According to the estimation results shown in Table 8, the conditional rates of convergence (ϑ) range from 0.088 to 0.181.[50]

The estimated coefficients of the spatially lagged dependent variable ($W^* lnY$) are significantly positive at either 1%, 5% or 10% significance levels across all the models (except model (4)). This finding reveals the positive spatial dependence of GDP per capita, that is, the GDP in one country is positively affected by its neighbouring countries' GDP. This result is consistent with Chica-Olmo, Sari-Hassoun, and Moya-Fernández (2020) evidence derived from 26 European countries over the period 1991–2015. Our finding further pro-

[47]The HT is the first generation test that ignores cross-sectional dependence. The CIPS is the second generation test that allows for cross-sectional dependence. The null hypothesis for these two tests is that a unit root exists.
[48]The mean of the series across panels is subtracted before performing the panel cointegration test in order to mitigate the impact of cross-sectional dependence (Levin, Lin, and Chu 2002; You and Lv 2018).
[49]The estimated coefficients of lnY_{-1} lie between the fixed effects estimate (which is downward biased) and the pooled OLS estimate (which is upward biased), indicating that the system GMM estimates are not subjected to significant finite sample bias (Zheng et al. 2013).
[50]The convergence rate ϑ is obtained using $\vartheta = -\ln(\tau)$ and τ is the coefficient of lnY_{-1} (Hao and Peng 2017).



2010



2018

Figure 1. Moran scatter plots of economic output in 2010 and 2018 using economic distance weight matrix. This figure plots spatially lagged GDP per capita against GDP per capita.

Table 5. Cross-sectional dependence test.

Variables	CD-test	Variables	CD-test
lnY	41.22***	*lnHYDR*	8.63***
lnK	14.31***	*lnCOAL*	10.13***
lnL	2.79***	*lnOIL*	20.34***
lnBIOM	21.20***	*lnINST*	3.14***
lnWIND	45.96***	*lnHC*	55.97***

The CD-test performs the null hypothesis of cross-sectional independence. *** denotes significant at the 1% level.

Table 6. Panel unit root tests.

Variable	Levels		First difference	
	HT	CIPS	HT	CIPS
lnY	0.9941	−1.297	0.5882***	−1.726**
lnK	0.9934	−1.401	0.3583***	−2.257***
lnL	0.9978	−0.615	0.2574***	−2.111***
lnBIOM	0.9972	−1.242	−0.0520***	−2.813***
lnWIND	0.9484**	−0.998	0.1517***	−2.591***
lnHYDR	0.9946	−1.755***	−0.2393***	−2.959***
lnCOAL	0.9883	−0.626	−0.2907***	−3.084***
lnOIL	0.9978	−1.459*	−0.1720***	−3.040***
lnINST	0.9865	−1.308	0.1034***	−2.875***
lnHC	0.9919	−0.619	0.9669*	−2.794***

***, ** and * denote a significance of 1%, 5% and 10%, respectively.

Table 7. Kao panel cointegration tests.

Kao test statistic	Model A (Biomass & waste)	Model B (Wind)	Model C (Biomass & waste and Wind)
Modified Dicky-Fuller t	1.2682*	2.4833***	1.2958*
Dicky-Fuller t	1.7962**	3.2362***	1.8285**
Augmented Dicky-Fuller t	3.2331***	4.5502***	3.1522***
Unadjusted modified Dicky-Fuller t	1.2365*	1.6531**	1.2172
Unadjusted Dicky-Fuller t	1.7668**	2.3181***	1.7556**

All test statistics are under null hypothesis of no cointegration. ***, ** and * denote a significance of 1%, 5% and 10%, respectively. In Model A, the series tested are *Y, K, L, BIOM, HYDR, COAL, OIL, INST* and *HC*. In Model B, the series tested are *Y, K, L, WIND, HYDR, COAL, OIL, INST* and *HC*. In Model C, the series tested are *Y, K, L, BIOM, WIND, HYDR, COAL, OIL, INST* and *HC*..

vides evidence for regional interconnectivity implying that the growth performance of developing countries depends on the growth rate of neighbouring regions.

The estimated parameters of electricity production from biomass & waste ($lnBIOM$) are positively and highly significant across all the models.[51] The estimated coefficients on wind power ($lnWIND$) are uniformly positive and consistent across all the models, albeit it is not statistically significant in two specifications. These results support the presence of the energy-led growth hypothesis for renewable energy sources.[52] Our findings are in line with Chen, Pinar, and Stengos (2020), Ito (2017) and Le, Chang, and Park (2020) who conclude that renewable energy is a driver of economic growth in developing countries. Our results further illustrate that individual renewable sources have positive impact on economic growth to different extents, and therefore it is necessary to disentangle the aggregate measures into disaggregate measures.[53] This is consistent with the evidence reported in Armeanu, Vintila, and Gherghina (2017) and Ohler and Fetters (2014).

[51]The countries which have biomass surpluses tend to use it rather locally in order to replace fossil fuels. In this regard, the positive and significant estimated parameters (*lnBIOM*) confirm that the local use of biomass can positively affect the economic growth of these countries with large local markets and suitable processing infrastructures.

[52]We further use the novel panel Granger non-causality test, developed by Juodis, Karavias, and Sarafidis (2021), to provide supportive evidence of one-way causality running from renewable energy sources to economic growth. This test accounts for cross-sectional dependence in the data series, efficiently estimates the panel Granger non-causality in heterogeneous or homogeneous panels and is robust for panel data with a moderate time dimension. So this test is suitable for our dataset. Under the null hypothesis, there is no causality in any cross-section units of the panel. Under the alternative hypothesis, there is causality in at least one cross-section unit. This test is applied on the first difference of the series under examination, because this test requires that all the variables must be stationary. The estimated results of the test with two lags are presented in Table A1. As shown, it suggests to reject the null hypothesis at either 1%, 5% or 10% significance levels. Therefore, the Granger causal relationships from individual renewable sources to economic growth is evidenced for the whole region under examination.

[53]The coefficients of *lnBIOM* range from 0.0133 to 0.0246, and the coefficients of *lnWIND* range from 0.0012 to 0.0034 (see Table 8).

Table 8. Dynamic SYS-GMM results using economic distance weight matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
lnY_{-1}	0.8683***	0.8344***	0.8909***	0.9158***	0.8855***	0.8431***
	(0.0186)	(0.0385)	(0.0253)	(0.0457)	(0.0313)	(0.0577)
lnBIOM	0.0133***	0.0146**			0.0143***	0.0246**
	(0.0046)	(0.0067)			(0.0056)	(0.0115)
lnWIND			0.0021**	0.0034***	0.0012	0.0023
			(0.001)	(0.0013)	(0.0015)	(0.002)
lnHYDR	−0.0193**	−0.0196**	−0.0088*	−0.0085*	−0.015**	−0.0239**
	(0.0095)	(0.0096)	(0.0053)	(0.0051)	(0.0068)	(0.0118)
lnCOAL	0.0052	0.0051	0.0027	0.0034	0.0012	−0.0038
	(0.0054)	(0.0062)	(0.0046)	(0.0052)	(0.0055)	(0.0056)
lnOIL	0.011	0.023*	0.0135	0.017*	0.011	0.0334
	(0.0138)	(0.0138)	(0.0113)	(0.0094)	(0.0136)	(0.0224)
lnK	0.0289	0.0131	0.0395*	0.0182	0.0284	−0.0391
	(0.0286)	(0.0294)	(0.022)	(0.0357)	(0.0344)	(0.0345)
lnL	0.1951***	0.1885**	0.1534***	0.0975*	0.1654***	0.3329***
	(0.0696)	(0.0819)	(0.0428)	(0.0562)	(0.062)	(0.122)
lnINST	0.0614***	0.0608***	0.0194	0.0335**	0.0325*	0.0519*
	(0.0201)	(0.0247)	(0.0156)	(0.0174)	(0.0183)	(0.0317)
lnHC	0.0254	0.0441	0.0524**	0.057*	0.0367	0.1331**
	(0.0436)	(0.0405)	(0.025)	(0.0322)	(0.0356)	(0.0677)
*W*lnY*	0.129**	0.1297***	0.069*	0.0161	0.081*	0.1289*
	(0.0551)	(0.052)	(0.0385)	(0.0489)	(0.0482)	(0.0772)
*W*lnBIOM*		−0.0286***				−0.0369
		(0.0089)				(0.0261)
*W*lnWIND*				−0.0074**		−0.0251***
				(0.0035)		(0.0081)
Constant	−0.3575	0.0931	−0.1017	0.289	−0.0173	0.703
	(0.5208)	(0.4715)	(0.3176)	(0.556)	(0.5552)	(0.6011)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Convergence rate (ϑ)	0.1412	0.181	0.1155	0.088	0.1216	0.1707
AR(1)	−2.42**	−2.28**	−2.48***	−2.38**	−2.46***	−1.98**
AR(2)	−0.42	−0.61	−0.22	−0.15	−0.48	−0.77
Hansen test	17.64	16.68	21.46	20.21	17.99	8.6
Nb of instruments	32	32	32	32	31	32
Nb of obs.	320	320	320	320	320	320

AR (1) and AR (2) denote Arellano-Bond first and second-order autocorrelation tests. Hansen test is the Hansen test of over identification restrictions. The convergence rate ϑ is obtained using $\vartheta = -\ln(\tau)$ and τ is the coefficient of lnY_{-1}. Standard errors are shown in parentheses. ***,**, and * denote a significance of 1%, 5% and 10%, respectively.

The estimated coefficient of the spatial lag for *lnBIOM* is significantly negative in model (2), and the coefficient of the spatial lag for *lnWIND* is significantly negative in both model (4) and model (6). These results suggest that the development of biomass & waste or wind power in neighbouring countries reduces the economic growth in home country. These results, to our knowledge for the first time, provide evidence of spatial spillover effects from renewable energy on economic growth for developing countries. These findings further justify that the heterogeneous spatial impacts of some particular renewable energy sources on economic growth may be masked by the total measure.

A possible explanation for negative spatial effects lies with the interactions between faster development of biomass & waste or wind power in nearby countries and the investment competition effect between the country and its neighbourhood. That is to say, faster development of biomass & waste or wind power in nearby countries benefiting from better renewable policy supports may trigger a re-location of foreign firms from a specific country to these countries.

For biomass, another possible explanation for this result is that a country in the development phase of the biomass sector may lead neighbouring countries to export raw or non-processed products, and large-scale production in the neighbouring countries could have a negative impact on their own potential growth.[54] Concerning the wind sector, another possible explanation for the negative

[54]Among the selected countries, the Russian Federation is one of the worldwide leaders in the production and export of industrial roundwood, with a large forest stock. The attractiveness of the neighbouring country confines the Russian wood industry to a primary specialization. It exports most of its industrial roundwood to China whose growing demand exceeds local production. This international position and the Russian fossil fuels-oriented energy policy do not encourage investment in local processing infrastructure allowing the deployment of the local use of biomass for energy purposes and a move upmarket in the associated value chain. The resulting increase in demand and employment of skilled labour related to this industry would drive human capital away from innovation activities within the biomass sector, reducing growth over the long run (Grossman and Helpman 1991; Young 1991).

spatial effects may be due to the displacement of environmentally harmful technologies. Concretely, the maturity of wind technology in surrounding countries may induce local country to increase its wind imports from the surrounding countries. A higher share of wind imports render wind power more competitive to alternative existing carbon-intensive fossil technologies, and thereby contributing to displace the latter in importing countries (Garsous and Worack 2022). The displacement of environmentally harmful technologies may subsequently result in economic losses (Xia and Song 2017).

Turning to the coefficients of traditional energy sources, the estimates, on the whole, show a negative and significant impact of hydroelectricity (*lnHYDR*) on economic growth, whereas a positive and insignificant impact of coal (*lnCOAL*) and oil (*lnOIL*)

on economic growth. Our result about the negative coefficient of hydroelectricity is inconsistent with the findings of Solarin and Ozturk (2015) and Ummalla and Samal (2018), showing that hydropower is a driving force to enhance the economic growth.[55] Our result is not surprising because hydroelectricity usage empirically proves to be harmful to the environment and by extension to the economic growth (Dash, Dash, and Sethi 2022). Our new evidence that is different from the finding of previous studies may be due to the use of different estimation techniques, different countries and sample period. The observed positive effect of oil (*lnOIL*) on economic growth is consistent with the evidence reported in Long et al. (2015) and Marques and Fuinhas (2012), suggesting that oil is a stimulus to economic growth.

The insignificant (with mixed signs) coefficient for coal (*lnCOAL*) is largely in line with the existing studies whose findings are at best inconclusive. Some studies lent their view in support of the coal as a driver of economic growth[56] while others hold the opposite view.[57] In fact, the inconclusive findings may be explained by two opposing forces and the net effect of coal on economic growth depends on the relative strength of each opposing force. On the one hand, coal is a relatively cheap energy source and thus remains the engine of economic growth (Marques and Fuinhas 2012). On the other hand, coal is the most carbon-intensive energy source which could damage the environment and therefore the economic expansion (Marques and Fuinhas 2012; Udi, Bekun, and Adedoyin 2020).[58] These results attest to the importance of considering the dissimilar and even contrary effects of disaggregated traditional energy sources on economic growth.

Conforming to the findings of many studies, a positive and significant effect of labour on economic growth is observed.[59] It implies that labour is a major driver behind the economic growth of developing countries. However, this is not the case for capital. As shown in Table 8, the coefficients of *lnK* are positive in models (1) - (5). These findings support the earlier studies[60] which reported that capital enhances economic growth. In contrast, the coefficient of *lnK* is negative in model (6). This result is consistent with the recent findings of Topcu, Altinoz, and Aslan (2020), suggesting that capital has a negative effect on economic growth.[61] Thus, the impact of capital on economic growth deserves more attention.

Next we turn to the coefficients of control variables. We observe that the estimated coefficients of institutional quality (*lnINST*) are positively and significantly at either 1%, 5% or 10% significance levels across all the models (except model (3)). This outcome is in accordance with a large body of literature[62] and supports the well documented insight that institutional quality is a critical driver of economic growth. We also find that human

[55]The studies on the nexus between hydroelectricity and economic growth are still scarce in the energy-growth literature (Dash, Dash, and Sethi 2022; Ummalla and Samal 2018).
[56]See Chen et al. (2022) and Long et al. (2015).
[57]See Marques and Fuinhas (2012) and Udi, Bekun, and Adedoyin (2020).
[58]The economic benefit of coal use may be outweighed by the economic costs of mitigating carbon emissions (Apergis and Payne 2010).
[59]See Koçak and Şarkgüneşi (2017) and Le, Boubaker, and Nguyen (2021).
[60]See Apergis and Payne (2012) and Koçak and Şarkgüneşi (2017).
[61]The negative impact of capital on economic growth may be due to the inadequacy of capital accumulation that is the most important limit to sustainable economic growth (Nweke, Odo, and Anoke 2017; Topcu, Altinoz, and Aslan 2020). Because the impact of capital accumulation on economic growth depends on the intensity of its determinants (such as savings and foreign direct investments), and the changes in these determinants could affect positively or negatively capital accumulation which in turn affect the economy as a whole (see Nweke, Odo, and Anoke (2017) for a detailed discussion).
[62]See e.g. Maruta, Banerjee, and Cavoli (2020) and Nawaz, Iqbal, and Khan (2014), among many others.

capital (*lnHC*) exerts a statistically significant impact on economic growth in models (3), (4) and (6). In addition, the positive effects of human capital are stable in all the models. Our results confirm the previous evidence[63], suggesting that human capital fosters economic growth.

Finally, to provide further validation of the baseline empirical estimates, we carry out an additional sensitivity analyses via alternative weight matrix specifications. Estimates of these robustness checks, reported in Appendix (see Table A2), show that the main results are quite similar to the baseline and do not depend on the choice of weight matrix.

IV. Conclusion and policy recommendations

Given the increasing investment in renewable energy in developing countries, this paper attempts to test the energy-led growth hypothesis for renewable energy sources for these countries. To this end, the present paper uses a balanced panel data of 32 lower/upper middle income countries over the period 2009 to 2019 and applies spatial dynamic techniques to investigate the impacts of disaggregate renewable energy sources on economic growth within a multivariate framework including the disaggregated non-renewable energy, capital, labour, institutional quality and human capital.

This paper provides statistically significant evidence for the positive impacts of electricity production from biomass & waste and wind power on economic growth of developing countries. Overall, these results validate the energy-led growth hypothesis for renewable energy sources. This study shows the first piece of evidence of spatial spillover effects from disaggregated renewable energy on economic growth for developing countries. Our results provide support on the existence of spatial dependence of economic growth across countries. Our analysis reveals the significantly negative impacts of hydroelectricity on economic growth. Our analysis also confirms the importance of labour, institutional quality and human capital in driving economic growth.

Our evidence of spatial spillover effects from renewable energy on economic growth points to the need to consider a spatial dependence in terms of renewable energy transition which has important policy implications for economic outcome. The spatial dependence of transition towards renewable energy is characterized by uneven distribution of renewable energy supply and demand[64], energy technological disparities in space[65], as well as competitive dynamics in technology development[66] (Noseleit 2018). These characteristics provide a rationale for government to pay special attention to the potential difficulties caused by country borders as spatial barriers that can hamper energy transition (Noseleit 2018). The spillover mechanism of energy transition further plays a crucial role in sustainable growth processes.

Given the extent to which the economic growth of developing countries depends on various renewable energy resources, policymakers should overcome current barriers to renewable energy deployment and pursue active policies to promote renewable energy for sustainable growth. First of all, government should play a fundamental role in how to finance the energy transition on both the supply side (R&D and infrastructures) and the demand side (education and communication to change individual and social preferences).[67] Second, in developing countries, the renewable energy sector refers to infant industries that do require particular forms of government assistance based upon specific instruments of industrial or sector-oriented policy[68] Third, energy policies directed at the diffusion of renewable energies should strengthen the entire value chain from the

[63]See Fang and Chen (2017) and Siddiqui and Rehman (2017).
[64]The imperfectly correlated renewable energy supply and demand across countries promotes the development of cross-border energy markets so as to share 'back-up' production capacities and meet excess demand (Abrell and Rausch 2016).
[65]The uneven development of new energy technology in space is responsible for the adoption and diffusion speed of renewable energy innovation across countries. The countries that are spatially proximate to the location of innovation may experience an ease technology diffusion, whereas, the countries that are far away from the innovation may experience substantial delay in adopting new technological solutions.
[66]Different domestic and foreign technologies compete in space may result in more complex spatial patterns of energy transition towards renewable sources.
[67]Initial investment costs are much more significant in emerging renewable energies, such as, wind (biomass) power, than in the conventional alternative. These financing costs might offset the 'natural' comparative advantage that developing countries may have.
[68]Such as, tax credits or exemptions, employment credits, privileged access to scarce factors of production, and provision of credit at below market rates..

manufacturer to the end user.[69] Finally, in the current globalized context where externalities, free-riding and public budget constraints play an important role, traditional policy tools such as taxes or subsides should be complemented with other solutions based on new financial engineering and leverage jointly with the restoration of missing markets (pollution permits).

Meanwhile, the policymakers should attach equal importance to energy security alongside renewable energy deployment.[70] The increasing pressure to decarbonize energy systems has triggered a strong interest in favour of the integration of renewable energy sources in electricity mix (Hache and Palle 2019; Radulescu and Sulger 2022). However, the integration of renewable energy sources in electricity mix poses energy security challenges for several reasons (Radulescu and Sulger 2022). First, large-scale integration of renewable energy sources may introduce additional uncertainty to an existing power system due to the intermittent nature of these sources (Das et al. 2018; Hache and Palle 2019).[71] In this context, a flexible power system is critical to ensure large-scale penetration of intermittent renewable energy sources (Das et al. 2018).[72] It is widely perceived that flexible backup unit[73] is an essential part of the solution to cope with the intermittency. Nevertheless, the subsidized renewable energy sources distort investment incentives for conventional backup capacity and thus the adverse investment effects of renewable energy sources may pose a threat to adequate electricity supply in the long-run (Liebensteiner and Wrienz 2020). Second, pursuing renewable energy transition may curtail energy sovereignty.[74] The pressure for fighting against climate change pushes the countries, in which renewable resource endowments are limited and energy system infrastructures are less developed, to integrate their power systems with neighbouring countries (Thaler and Hofmann 2022). The cross-border power systems allow improving reliability and availability of electricity. Despite this, the integration into cross-border power systems require common rules and lead to reduced autonomy in energy policymaking (Thaler and Hofmann 2022). Third, renewable energy transition policies may induce new energy security challenges. The transition towards renewable energy may result in geopolitical consequences, which are less conflictual than those of fossil fuels, by transforming patterns of cooperation and conflict between countries (Hache 2018; Scholten et al. 2020). The expansion of renewable energy technologies could lead to new interdependences, especially, dependences to critical minerals and metals (Hache 2018; Scholten et al. 2020). The dependences to critical minerals and metals may exacerbate competition for access to these materials among countries that compete for industry in renewable generation technologies (Scholten et al. 2020).

The current limitations regarding available data prevent the extension of analysis to additional years and to more countries, and prevent the investigation of other renewable energy sources across developing countries, and therefore it is left for further research.

Acknowledgments

The authors gratefully acknowledge the financial support from the MOMENTOM (MOlecules and Materials for the ENergy of TOMorrow) project, a Strategic Research Initiative of the Université Paris-Saclay. We are also grateful for comments from colleagues in GDRI International Development Economics conference at Université Clermont Auvergne, 15-16 November 2018 in Clermont-

[69]Because the diffusion of renewable energies not only depends on the improvement of scientific and technical knowledge, but also depends on the potential adopters, the endowment of natural resources, the development level and the policies that are practiced.

[70]Achieving energy security remains a difficult task for developing countries (Gyeltshen 2022). Although the issue of energy security is pervasive in the literature, there is no consensus on the definition of energy security (Guivarch and Monjon 2017). The definitions of energy security have evolved over time, from the initial concept of securing oil supply, later extended to secure the whole energy supply system, recently, the concept has encompassed global warming and sustainability aspects (Gyeltshen 2022).

[71]The intermittency problem has been a major constraint for transitioning to an energy system based primarily on renewable energy sources, given that power supply must match power demand at any time (Helm and Mier 2021).

[72]A power system is flexible if it can manage production or consumption in support the power system stability (Loisel et al. 2022). The sources of power system flexibility include thermal power plants, energy storage, demand-side management and grid interconnections (Das et al. 2018; Loisel et al. 2022).

[73]For example, gas or coal fired power plants.

[74]Energy sovereignty is defined as a nation's ability and authority to control, regulate and manage its own energy (Hansen and Moe 2022; Jewell, Cherp, and Riahi 2014).

Ferrand. In particular, we sincerely thank the anonymous reviewers for the constructive comments and suggestions, which helped us to substantially improve our manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The work was supported by the Université Paris-Saclay.

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Appendix

Table A1. Juodis, Karavias and Sarafidis (2021) panel causality test.

Null hypotheses	Statistics	
	HPJ Wald test	P-value
BIOM does not Granger cause Y	6.934**	0.0312
WIND does not Granger cause *Y*	5.794*	0.0552
BIOM and WIND do not Granger cause *Y*	37.84***	0.0000

***,**, and * indicate rejection of the null hypothesis at 1%, 5% and 10%. H_0: no causality in any cross-section units. H_1: causality exists in at least one cross-section unit.

Table A2. Dynamic SYS-GMM results using queen contiguity matrix – robustness checks.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
lnY$_{-1}$	0.9055***	0.8832***	0.8901***	0.892***	0.8664***	0.8764***
	(0.036)	(0.0297)	(0.043)	(0.0399)	(0.0199)	(0.0331)
lnBIOM	0.011**	0.013***			0.0148***	0.0118**
	(0.0055)	(0.0052)			(0.0055)	(0.0053)
lnWIND			0.0028**	0.0044***	−0.0038	−0.0024
			(0.0012)	(0.0017)	(0.0032)	(0.0017)
lnHYDR	−0.0037	−0.0219***	−0.0062	−0.0101*	−0.0154***	−0.0051
	(0.0064)	(0.0086)	(0.0062)	(0.0057)	(0.0052)	(0.0085)
lnCOAL	−0.0073	−0.0044	0.0003	−0.0146***	−0.0068	−0.0158
	(0.0054)	(0.0044)	(0.0041)	(0.0059)	(0.0051)	(0.0108)
lnOIL	0.0117	0.0343***	0.0131	0.0326**	0.0308***	0.031***
	(0.014)	(0.0125)	(0.0152)	(0.0149)	(0.0107)	(0.0125)
lnK	0.0454	0.0187	0.0444*	0.0155	0.0235	0.0252
	(0.0325)	(0.0262)	(0.0266)	(0.0451)	(0.0354)	(0.0294)
lnL	0.1526**	0.2004***	0.0962**	0.1325**	0.1624***	0.1834**
	(0.0764)	(0.0489)	(0.0473)	(0.0635)	(0.055)	(0.0775)
lnINST	0.0433*	0.0816***	0.0019	0.0369	0.0925***	0.0382
	(0.0262)	(0.0234)	(0.0231)	(0.0304)	(0.0272)	(0.0293)
lnHC	0.072*	0.1512***	0.0931***	0.0921	0.0813*	0.0867
	(0.0415)	(0.0607)	(0.0366)	(0.0653)	(0.0485)	(0.0654)
*W*lnY*	0.0026**	0.0025**	0.0007	0.0011	0.0016	0.0019*
	(0.0012)	(0.0013)	(0.0009)	(0.0011)	(0.0012)	(0.0012)
*W*lnBIOM*		−0.0031**				0.0009
		(0.0014)				(0.0018)
*W*lnWIND*				−0.0031***		−0.0022**
				(0.0007)		(0.001)
Constant	0.05	0.3607	0.3862	0.4743	0.4938	0.5184*
	(0.3032)	(0.3063)	(0.3185)	(0.3889)	(0.4967)	(0.2988)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Convergence rate (ϑ)	0.0993	0.1242	0.1164	0.1143	0.1434	0.1319
AR(1)	−2.38**	−2.30**	−2.46***	−2.23**	−2.33**	−2.41**
AR(2)	−0.42	−0.73	−0.24	−0.25	−0.57	−0.57
Hansen test	13.85	17.66	20.77	12.35	16.37	9.86
Nb of instruments	32	32	32	32	32	32
Nb of obs.	320	320	320	320	320	320

AR (1) and AR (2) denote Arellano-Bond first and second-order autocorrelation tests. Hansen test is the Hansen test of over identification restrictions. The convergence rate ϑ is obtained using $\vartheta = -\ln(\tau)$ and τ is the coefficient of *lnY*$_{-1}$. Standard errors are shown in parentheses. ***,**, and * denote a significance of 1%, 5% and 10%, respectively.