

Article

Comparing the Environmental and Energy Kuznets Curves in Japan: A Spatial Econometric Approach

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Abstract

This study investigates the dynamic interplay among CO₂ emissions, electricity consumption, and economic growth in Japan following the 2016 electricity market liberalization. The purpose is to determine whether the Environmental Kuznets Curve (EKC) and Energy-Environmental Kuznets Curve (EEKC) hypotheses hold when accounting for spatial dependencies across Japan's 47 prefectures, and how the 2016 market reforms have influenced these relationships. We test two primary hypotheses: first, that Japan has surpassed the EKC turning point, resulting in a downward trajectory where CO₂ emissions decline as economic growth continues; and second, that liberalization has facilitated the adoption of renewable energy, leading to an inverted U-shaped relationship between growth and electricity consumption. Using spatial econometric methods, the analysis reveals that Japan has successfully decoupled growth from emissions, while finding an inverted U-shaped relationship between economic growth and electricity consumption. These findings suggest that policymakers should emphasize regional integration and sector-specific green innovation to sustain this progress.

Keywords: electricity market liberalization; CO₂ emissions; electricity consumption; spatial econometrics

1. Introduction

To foster competition and promote renewable energy, Japan fully liberalized its electricity retail market on 1 April 2016. Before this date, the Japanese electricity market was dominated by ten regional electric companies, including Tokyo Electric Power Company (TEPCO) and Kansai Electric Power Company (KEPCO). Electricity was only available to consumers through these ten companies; consequently, electricity demand data were available only for the regions covered by the ten regional monopolies. After 2016, new electric utilities, often provided by Power Producers and Suppliers (PPS), began competing with the traditional monopolies, enabling the availability of electricity demand data at the prefectural level.

This 2016 electricity market liberalization is often called the “full liberalization of the electricity retail market” since the liberalization enabled companies other than the 10 regional monopolistic power companies to be able to directly sell electricity to the consumers. The objectives of electricity market liberalization encompassed the promotion of technological innovation to enhance energy efficiency, the empowerment of consumers to



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select electricity providers aligned with their preference for renewable energy, and the facilitation of market entry for emerging renewable energy producers within the electricity supply sector.

Thus, we expect that the 2016 electricity market liberalization has promoted the use of renewable energy, and that the resulting economic growth after 2016 has contributed to reductions in both CO₂ emissions and electricity consumption. However, to date, few studies have addressed the effects of the 2016 liberalization of Japan's electricity market on the dynamic interplay among CO₂ emissions, electricity consumption, and economic growth. Therefore, the objective of this study is to fill this research gap by investigating these relationships.

Previous studies support the existence of the Environmental Kuznets Curve (EKC) in Japan, specifically in the relationship between CO₂ emissions and economic growth [1–3]. However, these studies focus only on the period prior to 2016 and do not employ spatial econometric models to account for spatial dependence or autocorrelation among neighboring regions. Given that the EKC appears to hold for Japan, it is expected that the country is already on a downward trajectory, with CO₂ emissions declining as economic growth continues.

"In contrast to studies on the EKC for Japan, no research has yet examined the relationship between energy demand and economic growth using the Energy EKC (EEKC) model, also known as the Energy Kuznets curve, although this hypothesis has been investigated in the broader Asia-Pacific region [4]. Most studies on electricity demand in Japan focus on the price elasticity of demand [5–7] and improvements in energy efficiency [8]. While some studies have investigated the carbon emissions and electricity demand in Japan [9,10], they have not used the EEKC model to analyze this relationship. Furthermore, these previous studies all typically rely on data from the 10 monopolistic utility regions, with very few utilizing the more detailed prefectural-level energy demand data that became available after 2016.

To address this research gap, this study investigates the dynamic interplay among CO₂ emissions, electricity consumption, and economic growth following the 2016 electricity market liberalization in Japan. Specifically, it examines whether the Environmental Kuznets Curve (EKC) and Energy-Environmental Kuznets Curve (EEKC) hypotheses hold when spatial dependencies across Japan's 47 prefectures are taken into account, and how the 2016 electricity market liberalization has influenced these relationships.

Based on these research questions, two hypotheses are tested. First, Japan has surpassed the EKC turning point, resulting in a downward trajectory in which CO₂ emissions decline as economic growth continues (H1). Second, the 2016 liberalization has facilitated the adoption of renewable energy, leading to an inverted U-shaped relationship between economic growth and electricity consumption (H2).

The contribution of this study is threefold. First, it is among the first to examine the impact of economic growth on CO₂ emissions and electricity consumption in Japan using prefectural-level panel data following the electricity liberalization in 2016. Second, the study employs Geographic Information System (GIS) data to account for spatial dependence among Japan's 47 prefectures. To date, no other studies have considered such spatial dependencies at the prefectural level to analyze the relationships among CO₂ emissions, electricity consumption, and economic growth, as prefectural-level electricity consumption data only became available in 2016. Most studies examining the Japanese electricity market have relied on regional data from the ten traditional regions: Hokkaido, Tohoku, Tokyo, Chubu, Kansai, Hokuriku, Chugoku, Shikoku, Kyushu, and Okinawa. Third, this study contributes to the literature on the Environmental Kuznets Curve (EKC) and the Energy Kuznets Curve (EEKC) by exploring how renewable energy promotion policies in-

fluence the EKC and EEKC differently, using Japan's electricity liberalization policy as a case study.

2. Methods

While Grossman & Krueger [11] are recognized as one of the first studies to investigate the relationship between pollution and economic growth under the Environmental Kuznets Curve framework, Suri & Chapman [12] extended the model to energy, using energy consumption as the dependent variable. They analyze energy consumption and GDP data for 33 countries across various regions from 1971 to 1991 and conclude that the downward trend in the inverted-U curve is linked to shifts in the trade of manufactured goods.

Building on this foundation, our research methodology is structured as follows:

- (i) **Data Collection and Temporal Scope:** We constructed a balanced panel dataset covering the 47 prefectures of Japan from 2016 to 2021. This period was selected because 2021 represented the most recent year for which consistent, high-quality data were available for all study variables at the time of data collection in 2024.
- (ii) **Model Selection:** We began by testing the Environmental Kuznets Curve (EKC) and Energy Kuznets Curve (EEKC) models using conventional fixed effects and random effects panel models. The Hausman test was utilized to determine the appropriate model, leading to the adoption of the fixed effects model.
- (iii) **Spatial Diagnostics:** We performed Moran's I and Geary's C tests on the baseline model to assess spatial autocorrelation. The results confirmed statistically significant spatial association at the 1% level across all years, justifying the use of spatial econometric models.
- (iv) **Spatial Estimation:** Based on these diagnostics, we estimated the relationships using three distinct spatial models: the Spatial Lag Model (SLM), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM), with the latter providing the best fit for our analysis.

Following the basic model introduced by Suri & Chapman (1998) [12], the theoretical model is expressed as follows:

$$env. impact = \beta_0 + \beta_1 gpp + \beta_2 gpp^2 + \sum_{i=3}^8 X_i + \varepsilon \quad (1)$$

In the EKC model, the dependent variable represents annual total CO₂ emissions (in metric megatons), while in the EEKC model, it represents annual total electricity consumption (in gigawatt hours).

X contains the control variables, selected based on previous research on EKC and EEKC. These include the annual temperature of each prefecture (Temperature), area of rice fields (Rice land), farmland other than rice fields (Farmland), population density, the number of construction firms (Constructor), and the number of workers in the manufacturing sector (Manufacture).

The effect of temperature is included in the model since studies have found a strong relationship between CO₂ emissions, energy use, and temperature [13,14]. Although the effect of temperature on CO₂ emissions has not been investigated in the case of Japan, Wakiyama et al. [10] found that an increase in average temperature led to lower average electricity consumption.

We include the effects of areas of rice fields and farmland in the model, as previous studies suggest the importance of considering agricultural land use in the EKC model [15–17]. These studies suggest that increased agricultural land use leads to greater

environmental impacts [14,15]. Therefore, we expect to consider the effects of changes in agricultural land use on CO₂ emissions and electricity consumption.

Population density was considered following Kostakis et al. [18], which finds that an increase in population density tends to lower CO₂ emissions. For the relationship between population density and energy use, Morikawa [19] finds that energy efficiency increases in urban areas with higher population density and that electricity consumption is higher in densely populated cities. Therefore, we anticipate that higher population density will negatively affect CO₂ emissions and electricity consumption.

The number of construction firms was included in the model since it is suggested that the building and construction sector accounts for 34% of global energy consumption and 37% of energy- and process-related CO₂ emissions [20]. Zhang et al. [21] examine the effect of economic growth on CO₂ emissions in the construction industry based on the Environmental Kuznets Curve (EKC). However, before this study, only a few studies have examined the effect of the number of construction firms on CO₂ emissions and energy consumption.

The decision to use the number of workers in the manufacturing sector is strongly supported by both theoretical and empirical evidence, particularly in the context of Japan. First, employment serves as a more accurate proxy for actual production scale and energy demand, as the number of workers directly correlates with operational activity and resource consumption. This relationship is especially relevant in Japan's manufacturing sector, where a small number of large firms (such as Toyota and Panasonic) dominate emissions output, while numerous small subcontractors contribute minimally. Studies such as Fujii et al. [22], Kaya et al. [23], and Zhou and Zhou [24] have demonstrated that workforce size is a stronger predictor of environmental impact than the number of enterprises in Japan. The worker-based model also better reflects Japan's unique industrial structure, in which keiretsu networks create concentrated production hubs surrounded by numerous small suppliers. By using employment data, our analysis more accurately captures the true relationship between manufacturing activity and CO₂ emissions in Japan.

Table 1 provides details of the variables used in this study. Equation (1) is initially tested using both conventional fixed-effects and random-effects panel models. Based on the results of the Hausman test, the fixed effects model is preferred and therefore adopted in this study. Based on the fixed effects model, the study employed Moran's I and Geary's C tests to examine spatial autocorrelation in the baseline model, to determine whether spatial econometric models are more appropriate than traditional econometric approaches for the analysis. The third nearest neighbor spatial weight matrix is used in the spatial analysis to account for Japan's unique geographical structure, which includes several island prefectures. The results of these tests, presented in Table 2, show that both CO₂ emissions and electricity consumption exhibit statistically significant spatial autocorrelation at the 1% significance level across all years (2016–2021). The positive values of Moran's I and Geary's C tests indicate a positive spatial association, meaning that prefectures with higher levels of electricity consumption and CO₂ emissions tend to influence and pollute their neighbouring prefectures. This finding underscores the importance of incorporating spatial dependencies into the analysis, as traditional models would fail to capture these regional spillover effects [25,26].

Thus, the current study applied three types of spatial econometric models. The first one is the spatial lag model (SLM) which can be expressed as:

$$env. impact_t = \rho W \sum_{j=1}^p env. impact_{t-p} + X_t \beta + \varepsilon_t \quad (2)$$

where ρ is the spatial autoregressive parameter, W is the spatial weight matrix, and $\varepsilon_t \sim N(0, \sigma^2)$ and is independent and identically distributed. This model assumes that

each region's environmental impact is affected by the weighted average of its neighboring environmental impacts.

Table 1. Description of variables.

Variable	Unit	Description	Name of the Source	Link to the Data Source
CO ₂	Mt (megaton/year)	Total CO ₂ emissions from all sectors in each prefecture	Current Estimates of CO ₂ Emissions by Sector)	https://www.env.go.jp/policy/local_keikaku/tools/suikai2.html (accessed on 20 December 2025)
Electricity	GWh (gigawatt/year)	Total electricity consumption in each prefecture	Electricity Demand by Prefecture	https://www.enecho.meti.go.jp/statistics/electric_power/ep002/results_archive.html#h28 (accessed on 20 December 2025)
GPP	Trillion JPY	Gross prefectural domestic product of each prefecture	The State of Prefectures and Municipalities)	https://www.e-stat.go.jp/regional-statistics/ssdsviiew/prefectures (accessed on 20 December 2025)
Temperature	Celsius	The arithmetic means of the monthly average temperatures for 12 months in each prefecture		
Rice land	Square meter	Total area of rice field subject to fixed asset taxation		
Farmland	Square meter	Total area of farmland other than the rice field subject to fixed asset taxation		
Population density	Number of people per square meter	The prefectural population divided by the total area of the residential area (m ²)		
Constructor	Number of firms	Number of firms in each prefecture per budget year		
Manufacture	Number of workers	Number of workers in the manufacturing sector as of June 1st of each survey year.		

The second is the spatial error model (SEM), which can be denoted as:

$$env. impact_t = X_t \beta + \varepsilon_t, \quad \varepsilon_t = \lambda W \sum_{j=1}^q \varepsilon_{t-j} + u_t \quad (3)$$

where λ and u_t are the spatial autocorrelation parameter and the spatially autocorrelated error term. This model assumes that the disturbance of one region is related to that of nearby regions.

Finally, we estimated the EKC and EEKC models with the spatial Durbin model (SDM), which can be written as Equation (4) below.

$$env. impact_t = \rho W \sum_{j=1}^p env. impact_{t-j} + X_t \beta + \theta W \sum_{k=1}^r X_{t-k} + \varepsilon_t \quad (4)$$

where θ is the spatial lag parameter of the explanatory variables. This model believes that both the lag of dependent and independent variables in neighboring regions affect the dependent variable of a given region.

Table 2. Moran's I & Geary's C Test.

Years	CO ₂ Emission		Electricity Consumption	
	Moran's I	Geary's C	Moran's I	Geary's C
2016	0.286 *** (0.002)	0.675 *** (0.002)	0.320 *** (0.000)	0.647 *** (0.003)
2017	0.292 *** (0.001)	0.662 *** (0.002)	0.319 *** (0.000)	0.648 *** (0.003)
2018	0.301 *** (0.001)	0.646 *** (0.001)	0.320 *** (0.000)	0.646 *** (0.003)
2019	0.301 *** (0.001)	0.648 *** (0.001)	0.325 *** (0.000)	0.637 *** (0.003)
2020	0.304 *** (0.001)	0.650 *** (0.001)	0.328 *** (0.000)	0.635 *** (0.003)
2021	0.322 *** (0.001)	0.624 *** (0.001)	0.325 *** (0.001)	0.639 *** (0.003)

*** $p < 0.01$.

Spatial Data

The shape file data used to create the spatial weights for the spatial econometric analyses are obtained from the Geospatial Information Authority of Japan [27]. Using this data, Figure 1 presents scatterplots of CO₂ emissions and electricity consumption at the prefectural level in Japan. The results reveal that metropolitan areas—particularly those in the Kanto and Kansai regions—consistently rank as the highest CO₂ emitters. These regions play a central role in Japan's economy, serving as hubs for industrial activities and urban services. Major metropolitan areas such as Tokyo, Yokohama, Saitama, Chiba, Osaka, Hyogo, Shiga, and Kyoto are located in these regions, contributing significantly to both economic output and environmental pollution [28]. Additionally, Hokkaido, located at the northernmost point of Japan and experiencing cold winters, exhibits higher electricity consumption due to increased heating demand, which in turn leads to elevated CO₂ emissions. This aligns with the broader literature on electricity consumption in colder climates, where heating demand significantly increases energy use and associated emissions [29].

The spatial dependence observed in the data suggests that highly polluted prefectures have a more significant impact on their neighboring prefectures. This is likely due to the spillover effects of emissions, where pollutants generated in one prefecture affect adjacent areas through atmospheric dispersion or shared infrastructure [30]. For instance, industrial activities in one prefecture may lead to increased emissions that spread to neighboring regions, exacerbating environmental degradation across a wider area. This finding highlights the need for regional cooperation in environmental policy-making, as the actions of one prefecture can have significant consequences for its neighbors. The results also underscore the critical role of fossil fuels in Japan's energy mix, which currently accounts for 83% of electricity production. This heavy reliance on fossil fuels not only contributes to high levels of CO₂ emissions but also leads to a strong spatial correlation between electricity consumption and environmental pollution. As Japan continues to confront the dual challenges of economic growth and environmental sustainability, these findings reinforce the importance of transitioning to nuclear energy and enhancing energy efficiency to mitigate the spatial spillover effects of pollution.

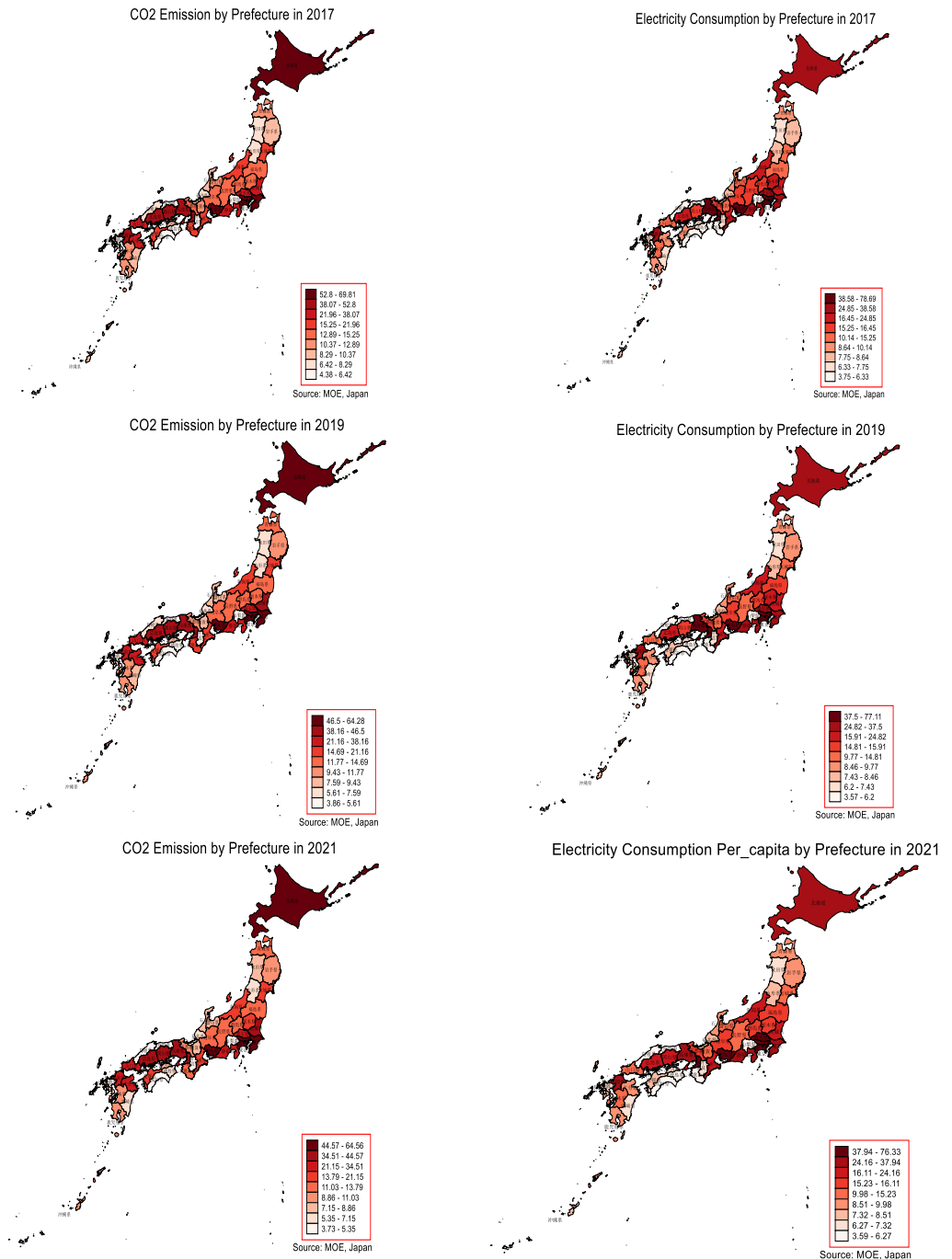


Figure 1. CO₂ emission and electricity consumption at prefecture level in Japan. 北海道: Hokkaido, 青森県: Aomori, 岩手県: Iwate, 宮城県: Miyagi, 秋田県: Akita, 山形県: Yamagata, 福島県: Fukushima, 茨城県: Ibaraki, 栃木県: Tochigi, 群馬県: Gunma, 埼玉県: Saitama, 千葉県: Chiba, 東京都: Tokyo, 神奈川県: Kanagawa, 新潟県: Niigata, 富山県: Toyama, 石川県: Ishikawa, 福井県: Fukui, 山梨県: Yamanashi, 長野県: Nagano, 岐阜県: Gifu, 静岡県: Shizuoka, 愛知県: Aichi (Nagoya is located in this prefecture), 三重県: Mie, 滋賀県: Shiga, 京都府: Kyoto, 大阪府: Osaka, 兵庫県: Hyogo, 奈良県: Nara, 和歌山県: Wakayama, 鳥取県: Tottori, 島根県: Shimane, 岡山県: Okayama, 広島県: Hiroshima, 山口県: Yamaguchi, 徳島県: Tokushima, 香川県: Kagawa, 愛媛県: Ehime, 高知県: Kochi, 福岡県: Fukuoka, 佐賀県: Saga, 長崎県: Nagasaki, 熊本県: Kumamoto, 大分県: Oita, 宮崎県: Miyazaki, 鹿児島県: Kagoshima, 沖縄県: Okinawa.

3. Results

Table 3 presents the results of the EKC model estimation for CO₂ emissions. In all three spatial econometric models, GPP is found to be negatively significant, suggesting that

Japan is already experiencing a downward trend in CO₂ emissions as GPP increases. This result is somewhat consistent with previous research findings that identified an inverted U-shaped relationship between CO₂ emissions and economic growth [1,3], based on data prior to 2016. Our results suggest that Japan has remained beyond the turning point, where CO₂ emissions continue to decline as GPP increases.

Table 3. CO₂ emissions model estimation.

co2_Mega	Fixed Effect	SEM	SLM	SDM
GPP	−1.227 *** (0.003)	−0.809 ** (0.035)	−0.794 ** (0.021)	−0.796 ** (0.038)
GPP ²	0.003 (0.185)	0.001 (0.642)	0.001 (0.491)	0.002 (0.387)
Temperature	0.014 (0.952)	0.107 (0.716)	0.130 (0.500)	1.270 ** (0.027)
Rice	0.002 *** (0.000)	0.002 *** (0.000)	0.002 *** (0.000)	0.002 *** (0.000)
Farm	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)
Population Density	−0.968 ** (0.023)	−0.787 ** (0.037)	−1.098 *** (0.002)	−0.632 * (0.092)
Constructor	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)
Manufacture	0.002 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)
W_GPP				−0.657 (0.199)
W_GPP ²				0.007 (0.040)
W_Temperature				−1.261 ** (0.030)
W_Rice Land				0.001 * (0.095)
W_Farm Land				−0.001 * (0.098)
W_Population Density				−1.630 ** (0.019)
W_Constructor				0.000 ** (0.037)
W_Manufacture				−0.000 ** (0.056)
Constant	4.671 (0.738)			
Hausman Test	27.25 *** (0.000)			
ρ, λ		0.406 *** (0.000)	0.303 *** (0.000)	0.330 *** (0.000)
σ^2		0.853 *** (0.000)	0.859 *** (0.000)	0.772 *** (0.000)
Observation	282	282	282	282
R_Squared	0.691	0.683	0.699	0.734
Log-likelihood		−384.013	−382.135	−367.797

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The log-likelihood values in the table suggest that the Spatial Durbin Model provides the best fit among the three spatial econometric models. Therefore, we rely on this model to interpret the effects of the other variables.

The temperature had a positive effect on CO₂ emissions, which may indicate that rising temperatures—particularly during Japan’s hot and humid summers—lead to increased energy demand for cooling. This, in turn, drives higher electricity consumption and CO₂

emissions. Given Japan's heavy reliance on fossil fuels for energy production, this relationship highlights the urgent need to transition to renewable and nuclear energy sources to mitigate the environmental impact of climate change [31]. Another probable reason for the increase in CO₂ emissions as temperatures rise is that ocean warming reduces the solubility of CO₂ [32]. Since Japan is a country surrounded by the sea, rising ocean temperatures may contribute to an increase in the amount of CO₂ released into the atmosphere.

Areas of rice and farmland had a contrasting effect on CO₂ emissions. While an increase in the rice fields led to a rise in CO₂ emissions, farmland had a negative impact on CO₂ emissions. This result is likely related to the way prefectural-level CO₂ emissions are estimated. All greenhouse gases are converted to CO₂ equivalents by multiplying the emissions of each gas by its respective Global Warming Potential (GWP) value [33]. Rice cultivation is recognized to emit greater quantities of methane compared to upland fields, with one unit of methane possessing a GWP 28 times greater than that of an equivalent unit of CO₂ emissions. Furthermore, in Japan, nearly 54% of the cultivated land consisted of paddy fields during the period from 2016 to 2020 [34].

Population density is negatively associated with CO₂ emissions, indicating that higher population density leads to lower per capita CO₂ emissions. This is likely because metropolitan areas such as Tokyo (東京都), Osaka (大阪府), and Nagoya enable more efficient use of infrastructure and resources. Densely populated areas benefit from centralized energy systems, efficient public transportation networks, and shared living spaces, all of which contribute to lower per capita electricity consumption and reduced CO₂ emissions. This result is consistent with Kostakis et al. [18], which finds an inverse relationship between population density and CO₂ emissions.

The number of construction firms and the number of workers in the manufacturing sector both had a negative influence on CO₂ emissions. Since these variables reflect economic activity, it is plausible that, similar to overall economic growth, the intensification of economic activity may have promoted the development and adoption of energy-saving technologies, which in turn contributed to the reduction of CO₂ emissions. Since the Paris Agreement in 2015, Japanese construction companies have been promoting Zero Energy Buildings (ZEBs) [35], which contribute to the reduction of CO₂ emissions and electricity consumption. It is plausible that climate mitigation efforts within the construction sector have also played a role in contributing to this outcome.

The spatial lag variables provide further insights into the regional dynamics of CO₂ emissions. The positive and significant coefficient in the SLM for the spatially lagged dependent variable (W_CO_2) indicates that an increase in CO₂ emissions in neighbouring prefectures leads to an increase in emissions in the home prefecture. This suggests that environmental degradation in one prefecture can spill over into adjacent regions, highlighting the need for coordinated environmental policies at the regional level. Conversely, the results in the SDM model reveal that the spatially lagged temperature variable ($W_Temperature$) has a negative impact on neighbouring prefectures, leading to a decrease in emissions in the home prefecture. This finding emphasizes the importance of localized efforts to address climate change, as small temperature changes can have significant regional impacts. Similarly, the spatially lagged population density variable ($W_Population\ Density$) in the SDM shows that an increase in population density in neighbouring prefectures reduces CO₂ emissions in the home prefecture. This suggests that urban planning strategies that promote high-density living and efficient public transportation can have far-reaching benefits, reducing emissions not only in the home prefecture but also in surrounding areas.

Next, we discuss the results of the EEKC model estimation for electricity consumption in Table 4. In all models, it is evident from the table that there is an inverted-U relationship between the electricity consumption and GPP. This result may suggest that, follow-

ing the liberalization of the electricity retail market in Japan, more regions began to adopt less energy-intensive technologies—such as renewable energy—which contributed to improved energy efficiency. Indeed, the proportion of renewable energy in the energy mix has shown a continuous annual increase since 2016, rising from 15% to 22% [36]. Moreover, the share of photovoltaic energy within the renewable sector has doubled between 2016 and 2021.

Table 4. Electricity consumption model estimation.

Electricity Consumption	Fixed Effect	SLM	SEM	SDM
GPP	0.398 *** (0.001)	0.380 *** (0.000)	0.395 *** (0.000)	0.393 *** (0.001)
GPP ²	−0.002 *** (0.009)	−0.002 *** (0.005)	−0.002 *** (0.007)	−0.002 *** (0.002)
Temperature	−0.205 *** (0.003)	−0.152 ** (0.015)	−0.192 ** (0.011)	−0.009 (0.962)
Rice	0.000 ** (0.045)	0.000 ** (0.020)	0.000 * (0.059)	0.000 * (0.065)
Farm	0.000 ** (0.045)	−0.000 ** (0.015)	−0.000 * (0.062)	−0.000 ** (0.050)
Population Density	−0.387 *** (0.002)	−0.392 *** (0.000)	−0.339 *** (0.003)	−0.223 * (0.057)
Constructor	0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)
Manufacture	0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.002)	−0.000 *** (0.058)
W_GPP				0.092 (0.561)
W_GPP ²				−0.001 (0.245)
W_Temperature				−0.114 (0.532)
W_Rice Land				0.000 ** (0.020)
W_Farm Land				−0.000 (0.110)
W_Population Density				−0.585 *** (0.008)
W_Constructor				0.000 ** (0.049)
W_Manufacture				−0.000 *** (0.002)
Constant	24.323 *** (0.000)			
Hausman Test	−153.78 * (0.096)			
ρ, λ		0.151 *** (0.005)	0.243 *** (0.001)	0.153 ** (0.029)
σ^2		0.084 *** (0.000)	0.082 *** (0.000)	0.075 *** (0.000)
Observation	282	282	282	282
R_Squared	0.603	0.602	0.599	0.639
Log-likelihood		−51.107	−49.703	−36.238

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The effects of variables other than GPP showed a similar influence on electricity consumption as in Table 3, except that an increase in temperature had a negative impact on energy demand. However, temperature was not statistically significant in the SDM model. The negative influence of temperature on energy demand is likely attributable to the fact that heating systems generally consume more energy than cooling systems [37]. Con-

sequently, rising temperatures may lead to a decrease in heating usage, particularly in Japan's colder regions.

Finally, as a robustness test, the EKC and EEKC models were estimated, including dummy variables for the years 2020 and 2021 to account for the effects of the COVID-19 pandemic. As more people stayed at home during the COVID-19 pandemic era due to quarantine measures, studies suggest that electricity consumption increased during the pandemic [38–40]. The results of the SDM, as presented in Table 5, indicate that CO₂ emissions were elevated in 2020 and 2021, corresponding with the period during which Japan was affected by the COVID-19 pandemic. Likewise, Table 6 demonstrates an increase in electricity consumption during the same years, corroborating previous studies that have documented a rise in energy use amid the pandemic. Furthermore, similar to the results reported in Tables 3 and 4, these tables show that the EKC exhibits a linear downward trend, whereas the EEKC follows an inverted U-shaped trajectory.

Table 5. CO₂ emissions model estimation with effects from the COVID-19 era.

CO ₂ Emission	Fixed Effect	SLM	SEM	SDM
GPP	−1.295 *** (0.003)	−0.683 ** (0.056)	−0.892 ** (0.024)	−0.693 ** (0.073)
GPP ²	0.003 (0.194)	0.000 (0.858)	0.001 (0.542)	0.001 (0.677)
Temperature	−0.024 (0.918)	0.080 (0.669)	0.085 (0.776)	1.295 ** (0.023)
Rice	0.002 *** (0.000)	0.002 *** (0.000)	0.002 *** (0.000)	0.002 *** (0.000)
Farm	−0.001 *** (0.002)	−0.001 *** (0.000)	−0.001 *** (0.003)	−0.001 *** (0.000)
Population Density	−0.73 (0.103)	−0.666 ** (0.062)	−0.721 * (0.060)	−0.555 * (0.142)
Constructor	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)	−0.001 *** (0.000)
Manufacture	−0.0001 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)
COVID_2020	0.335 (0.253)	0.914 *** (0.000)	0.012 (0.970)	0.684 * (0.075)
COVID_2021	0.519 (0.684)	1.022 *** (0.000)	0.295 (0.385)	0.646 *** (0.000)
W_GPP				−0.481 (0.414)
W_GPP ²				0.005 (0.149)
W_Temperature				−1.267 ** (0.029)
W_Rice Land				0.001 * (0.055)
W_Farm Land				−0.000 (0.182)
W_Population Density				−1.177 (0.127)
W_Constructor				0.000 (0.640)
W_Manufacture				−0.000 (0.120)
COVID_2020				−0.006 (0.980)
COVID_2021				−0.006 (0.990)
Constant	6.299 (0.684)			

Table 5. Cont.

CO ₂ Emission	Fixed Effect	SLM	SEM	SDM
Hausman Test	40.87 *** (0.000)			
ρ, λ		0.367 *** (0.000)	0.400 *** (0.000)	0.310 *** (0.000)
σ^2		0.799 *** (0.000)	0.851 *** (0.000)	0.767 *** (0.000)
Observation	282	282	282	282
R_Squared	0.694	0.723	0.685	0.739
Log-likelihood		−373.624	−383.553	−366.223

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Electricity consumption model estimation with effects from the COVID-19 era.

Electricity Consumption	Fixed Effect	SLM	SEM	SDM
GPP	0.352 *** (0.005)	0.366 *** (0.001)	0.347 *** (0.002)	0.467 *** (0.001)
GPP ²	−0.002 ** (0.014)	−0.002 *** (0.003)	−0.001 ** (0.011)	−0.002 *** (0.002)
Temperature	−0.228 *** (0.001)	−0.161 *** (0.008)	−0.222 *** (0.002)	−0.008 (0.961)
Rice	0.0002 *** (0.008)	0.0002 *** (0.001)	0.0002 ** (0.011)	0.0001 ** (0.034)
Farm	−0.0001 (0.257)	−0.00001 (0.155)	−0.0001 (0.261)	−0.0001 ** (0.054)
Population Density	−0.241 ** (0.061)	−0.239 ** (0.032)	−0.244 ** (0.034)	−0.176 (0.057)
Constructor	0.0002 *** (0.000)	−0.0002 *** (0.000)	−0.0002 *** (0.000)	−0.0002 *** (0.000)
Manufacture	0.000 *** (0.003)	−0.00001 *** (0.000)	−0.00001 *** (0.009)	−0.000 ** (0.051)
COVID_2020	0.197 ** (0.020)	0.278 *** (0.000)	0.167 ** (0.043)	0.394 ** (0.043)
COVID_2021	0.316 *** (0.000)	0.339 *** (0.000)	0.294 *** (0.001)	0.316 *** (0.008)
W_GPP				0.310 * (0.090)
W_GPP ²				−0.003 ** (0.014)
W_Temperature				−0.122 (0.495)
W_Rice Land				0.0003 *** (0.005)
W_Farm Land				−0.0001 (0.265)
W_Population Density				−0.378 (0.113)
W_Constructor				−0.0000 (0.390)
W_Manufacture				−0.0000 *** (0.004)
COVID_2020				0.046 (0.701)
COVID_2021				0.042 (0.765)
Constant	17.673 *** (0.000)			
Hausman Test	−89.02 * (0.082)			

Table 6. Cont.

Electricity Consumption	Fixed Effect	SLM	SEM	SDM
ρ, λ		0.197 *** (0.005)	0.187 ** (0.010)	0.0872 (0.227)
σ^2		0.077 *** (0.000)	0.079 *** (0.000)	0.072 *** (0.000)
Observation	282	282	282	282
R_Squared	0.623	0.634	0.621	0.668
Log-likelihood		−41.513	−44.554	−29.601

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussions

Our findings regarding the linear inverse relationship between economic growth and CO₂ emissions align with recent evidence from other developed nations that have achieved decoupling through structural economic shifts and renewable energy adoption. While foundational global studies such as Suri and Chapman [12] established the theoretical basis for the EKC across 33 countries, contemporary research by Kostakis et al. [18] confirms that such trends continue to be observed across various cross-correlated countries. Additionally, the downward trajectory in emissions we identified within Japan's manufacturing and construction sectors mirrors the global empirical results reported by Zhang et al. [21]. Studies across Europe and the OECD have identified similar downward trends, often attributing them to green technology investments and the transition toward service-oriented structures [41].

The inverted U-shaped relationship observed in the Energy Kuznets Curve (EEKC) mirrors patterns in emerging economies, where initial expansion drives energy demand before efficiency improvements, accelerated by market liberalization, reduce consumption. Recent work by Çelik and Börü [42] supports the EKC hypothesis in emerging contexts, highlighting the critical role of trade openness and renewable energy integration. Our study distinguishes itself by explicitly accounting for spatial dependence; while traditional cross-country studies often overlook regional spillover effects, Wang et al. [43] and Cao et al. [44] confirm that environmental and energy outcomes are significantly influenced by neighboring areas. This reinforces the notion that national-level policy success depends heavily on the harmonization of regional strategies, a factor consistent with findings in other geographically constrained, industrialized nations.

5. Conclusions

The study examined the relationship between CO₂ emissions, electricity consumption, and economic growth using environmental and energy Kuznets curve models, following the liberalization of Japan's electricity market in 2016. This study employed a spatial econometric model to account for interregional effects among Japan's 47 prefectures. Using gross prefectural product (GPP) as a proxy for economic growth, the study found a linear inverse relationship between economic growth and CO₂ emissions, while an inverted U-shaped relationship was observed between economic growth and electricity consumption.

The downward-sloping EKC suggests that Japan has already entered a phase where economic growth no longer results in increased CO₂ emissions. This decoupling provides policymakers with a strategic opportunity to strengthen decarbonization policies without compromising economic development. Continued support for energy-efficient technologies and low-carbon innovations, particularly in sectors such as manufacturing and construction, should be prioritized to sustain and accelerate this trajectory. Meanwhile, the inverted U-shaped relationship observed between economic growth and electricity consumption suggests that the 2016 electricity market liberalization may have intensified com-

petition among electricity providers, thereby contributing to a more uniform distribution of electricity consumption nationwide.

The spatial spillover effects identified in the models, particularly the influence of neighboring prefectures' emissions and demographic characteristics, highlight the importance of inter-prefectural coordination in reducing CO₂ emissions and electricity consumption. National climate and energy policies should incorporate mechanisms that facilitate regional cooperation, ensuring that climate mitigation and energy efficiency efforts are harmonized across administrative boundaries to maximize their effectiveness.

These results provide specific guidance for economic practice and regional governance in Japan. Given the significant spatial spillover effects identified in our analysis, environmental policy should shift from a prefecture-by-prefecture approach to a regional coordination model, in which policymakers incentivize joint-prefectural energy grids to balance load and reduce the reliance on fossil-fuel backup in neighboring areas. Furthermore, as industrial activity in manufacturing and construction is effectively decoupling from emissions, economic policy should continue to provide fiscal incentives and tax credits for firms that adopt Zero Energy Building (ZEB) standards and low-carbon production technologies. Finally, the inverted U-shaped relationship regarding electricity consumption suggests that market competition drives efficiency, indicating that regulatory bodies should continue lowering barriers to entry for renewable energy providers, particularly in regions where electricity demand remains sensitive to economic expansion.

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