Three Essays on Energy Policy, Climate Change, and Economic Development

By

Soonpa Hong

Dissertation

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

IN PUBLIC MANAGEMENT

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Committee in charge:

Professor Chungeun Yoon, Supervisor

Professor Yeong Jae Kim

Professor Seohyun Lee

Professor Dongil Lee

Dr. Ki Seon Cho

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ABSTRACT

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By

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(Chapter 1)

Renewable energy (RE) electricity plays a crucial role in addressing climate change but has limitations, such as intermittent production, high costs, and site constraints. South Korea transitioned its RE support system from a feed-in tariff (FIT) to a renewable portfolio standard (RPS) in 2012. This study evaluates the impact of the FIT-to-RPS transition on cost reduction for non-photovoltaic RE technologies (RETs), i.e., onshore wind power, bioenergy power, small hydropower, and fuel cell power, using a learning curve model. The results indicate that the FIT-to-RPS transition did not have a significant positive impact on cost reduction for onshore wind power, bioenergy power, or small hydropower, as the results show negative learning rates (LRs) during both FIT and RPS periods. The analysis suggests that the positive learning effect was hindered by the gradual depletion of sites favourable to RE power plants as more RE power plants were installed. However, fuel cell power, which is not affected by land availability, increased the LR from 1.4% to 3.5%.

This study has policy implications, such as improving excessive regulations and procedures that hinder the installation of RE power plants on sites with good condition.

(Chapter 2)

Economic growth, CO_2 emissions, and energy mix are interrelated, and their relationship has been analysed using various dynamic models. The Vector Autoregressive (VAR) model, treating all factors as endogenous, has been commonly used to study this relationship. However, reduced form VAR, which do not account for contemporaneous effects, may misrepresent the impact of energy policies. In contrast, the Structural VAR (SVAR) model which include contemporaneous effects, provide a more accurate evaluation of energy policy impacts. This study applies both reduced form VAR (IRF) and SVAR (OIRF) to South Korea and Japan. The IRFs from reduced form VAR indicate that in South Korea, the electricity mix does not causally affect CO_2 emissions, while both

fossil fuel and renewable electricity positively affect CO2 emissions in Japan. However, OIRFs from SVAR reveal that fossil fuel electricity significantly increases CO_2 emissions in both countries, while renewable electricity significantly reduces emissions in Japan. These findings suggest that SVAR provides a more accurate assessment of energy policies' environmental impacts than reduced form VAR, warranting caution with VAR results.

(Chapter 3)

This study examines the impact of the energy mix and economic growth on CO_2 emissions in 12 countries with nuclear power plants and 10 countries without, among OECD members, from 1971 to 2021, utilizing a dynamic panel ARDL model. The findings support the Environmental Kuznets Curve (EKC) hypothesis in countries with nuclear power but not in those without. Replacing fossil fuel electricity (FE) with renewable electricity generation (RE) or nuclear energy generation (NE) significantly lowers CO2 emissions in both groups in the long-run, and RE proves more effective than NE in nuclear-powered nations. Moreover, substituting FE with RE shows greater emissions reduction in countries lacking nuclear power plants. While trade openness has insignificant effect, population growth exerts a notable influence in both groups. To check the robustness of the ARDL results, same ARDL model with sub-sample group was also conducted, and the analysis of the sub-sample group shows similar results to those of the original ARDL results. The policy implications are that economic growth contributes to emissions reduction in the long-run for countries with nuclear energy, but this benefit is absent in countries without nuclear power, stressing the need for additional policy measures to curtail emissions.

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(Chapter 1) Comparing Feed-in Tariff and Renewable Portfolio Standard in South Korea: Cost Reduction Impact on Non-Photovoltaic Renewable Electricity

1 Introduction

Climate change is emerging as one of the most critical types of risk worldwide and thus requires a global response [1,2]. To address climate change, greenhouse gas reduction is crucial and greenhouse gases are largely generated in the energy sector [3]. Expanding the use of renewable energy (RE) in the energy sector is an important policy task for reducing of greenhouse gas emissions. Compared with fossil fuel technology, RE technologies (RETs) have several advantages such as reducing greenhouse gas emissions, decreasing pollutant emissions, and promoting the growth of new energy industry. However, there are various constraints on the expansion of RE, including high costs compared to fossil fuels, site constraints, and intermittent production [4].

To promote the expansion of RETs, governments have formulated and implemented various RET deployment and support policies [5]. In the field of electricity, the most representative systems for promoting RET electricity (RET-E) are feed-in tariff (FIT) and renewable portfolio standard (RPS). RE support policies can be considered within the broader category of energy policies, and the fundamental goal of energy policies in South Korea is to enhance energy security [6]. Energy security can be defined as the sustainable supply of a large amount of energy at an affordable price with little impact on the environment [7,8]. RE support policies must address the dual challenge of subsidizing the high costs associated with RETs, a known drawback, while also ensuring affordable energy prices from an energy security perspective. Therefore, an ideal RE support policy is one that deploys more RETs at low costs. The deployment of RETs at a low cost is crucial for reducing financial burdens and ensuring sustainable deployment. South Korea implemented FIT from 2002 to 2011 and transitioned to an RPS system in 2012. The FIT-to-RPS transition aimed to generate more RET-E at a lower price, essentially aiming to achieve grid parity at a more rapid pace. FIT and RPS systems are differentiated as price- and quantity-based schemes, respectively. Many countries have operated FIT or RPS systems, and there have been ongoing theoretical and empirical discussions comparing their effectiveness [9-16,4]. Unlike most other countries, South Korea's use of both FIT and RPS systems makes it a valuable subject for empirical analysis[1]. The impact of the FIT-to-RPS transition on the achievement of the grid parity of photovoltaics has already been studied [4]. Hong et al. [4] reported that the RPS system is much more effective than the FIT system in achieving grid parity for photovoltaics; the learning rates for photovoltaics during the FIT and RPS periods were -0.28% and

[1] To the best of my knowledge, as of now, South Korea and Japan are the only countries which have undergone a comprehensive and decisive transition from FIT to RPS system or, conversely, within their RE support systems.

18.44%, respectively. Meanwhile, the current research focuses on examining how the transition has affected non-photovoltaic RETs, namely, onshore wind power, bioenergy power, small hydropower, and fuel cell power, in terms of reducing the cost of RET-E generation. In this analysis method, a learning curve model is used; notably, with the cumulative increase in deployment or capacity, the average cost decreases due to learning effects. By calculating the learning rate (LR), we can determine how quickly the average cost decreases. If the LR differs between the FIT and RPS scheme periods, it is possible to assess which scheme is more effective at reducing costs.

The results of the analysis indicate that for fuel cell power, the RPS system has a significant effect on cost reduction compared to the FIT system, which is consistent with the analysis results for photovoltaics of Hong et al. [4]. However, for onshore wind power, bioenergy power, and small hydropower, the RPS system does not demonstrate clear superiority over the FIT system in terms of cost reduction; the learning rates for the three RETs were negative during both the FIT and RPS periods, which is not consistent with the analysis results for fuel cell power and photovoltaics [4].

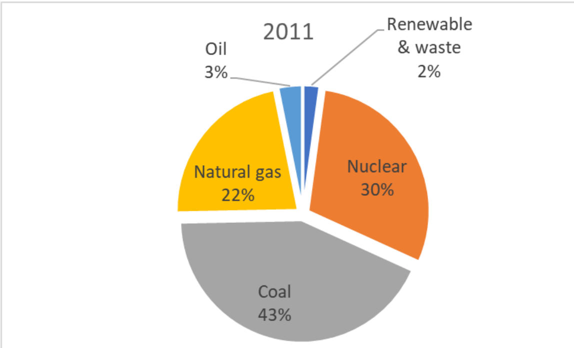
This study also explores the reasons behind these different results for fuel cell power and the other three RETs, and policy implications are derived accordingly. One significant reason is that in the case of onshore wind power, bioenergy power, and small hydropower, as more RE power plants are installed, sites with good conditions for RE generation are becoming scarce, thereby making cost reductions more challenging. In response, regulatory improvements are recommended to alleviate land availability constraints for RE power plants as a policy implication.

This study contributes significantly to the literature by empirically comparing the effects of FIT and RPS systems on the non-photovoltaic RETs, utilizing the case of South Korea where both systems have been implemented. The effectiveness of the two systems is compared in an empirical context, thereby contributing to academic discussions and providing policymakers with crucial insights into the effects of both systems.

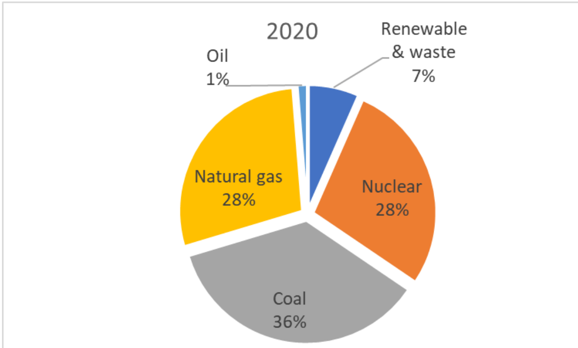
Figure 1 shows the electricity mix in South Korea in 2011 and 2020. It is evident that from 2011 to 2020, the proportion of 'renewable and waste' electricity increased significantly from 2% to 7%. Moreover, an examination of the composition within the 'renewable and waste' electricity category shows that between 2011 and 2020, the proportion of electricity generated from photovoltaic and bioenergy sources significantly increased, totalling 47% and 22%, respectively.

The rest of this study is structured as follows. An overview of the FIT and RPS schemes in

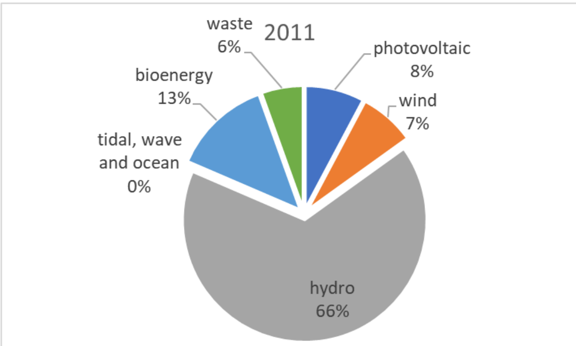
South Korea is provided in Section 2, a literature review is provided in Section 3, and the methodology and data are explained in Sections 4 and 5, respectively. The results and corresponding discussion are presented in Section 6, and the conclusions and policy implications are provided in Section 7.



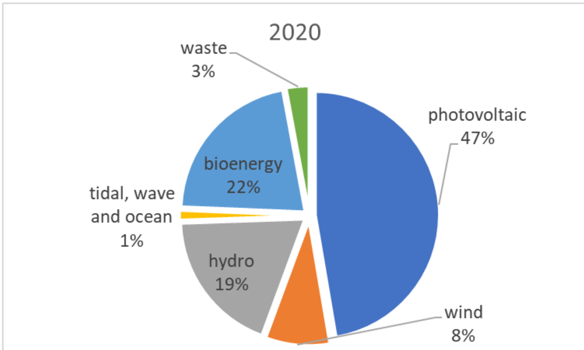
(a) Electricity mix in 2011



(b) Electricity mix in 2020



(c) Composition of renewable & waste electricity in 2011



(d) Composition of renewable & waste electricity in 2020

Figure 1 Electricity mix in South Korea (source: OECD)

2 Overview of the FIT and RPS schemes in South Korea

South Korea, which imports all petroleum and natural gas, introduced the FIT scheme in 2002 to enhance its energy security by expanding the deployment of RE [17]. The FIT scheme is a price-based approach in which the government sets the price (i.e., standard price) for RET-E. Based on this fixed price (standard price), the deployed quantity of RET-E is determined by the market. The government purchases RET-E at the standard price for 15 years. While the amount of RET-E generation is market driven and inherently uncertain, the advantage lies in the stability given by the fixed price, i.e., the standard price, which enables RE project developers to reliably install RE power plants. Meanwhile, depending on the type of RETs and the location of deployment, the government differentiates the standard prices of RET-E to encourage the deployment of less economically viable RET-E (Figure 2). The government sets the standard price of RET-E to be higher than the anticipated electricity market price (i.e., system marginal price (SMP)) and periodically adjusts it to account for cost fluctuations due to technological advancements and other factors such as policy objectives. Since 2008, South Korea's FIT scheme has faced significant financial burdens for photovoltaic deployment, and the deployment rate of RETs under the FIT scheme had been very low. Therefore, continuing the FIT scheme was deemed unsustainable. Consequently, in 2012, South Korea transitioned to an RPS scheme based on competition among different RET types [18].

Figure 2 Standard prices for RETs in the FIT scheme as of 2007 (source: Korea New and Renewable Energy Center (KNREC)) * Note: Small hydropower represents the '1-5 MW' category. Photovoltaics represent the '30-200 kW' category. SMP_high: highest SMP during 2003-2007. SMP_low: lowest SMP during 2003-2007.

The RPS scheme is a quantity-based system in which the government sets the amount of RET-E, and the market determines its price. Therefore, while the quantity of RET-E may remain stable, the fluctuating prices can negatively impact the investment environment necessary for the stable development of RE power plants. Under the RPS scheme, RE power plants are issued renewable electricity certificates (RECs) equivalent to the amount of renewable electricity they generate. These certificates can be sold in the REC market to generate additional revenue (Figure 3). Essentially, RE power plants earn revenue by selling renewable electricity in the electricity market and their corresponding RECs in the REC market.

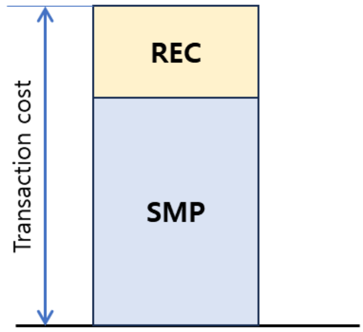


Figure 3 Transaction cost (or transaction revenue) of RET-E under the RPS scheme

Since the RPS scheme promotes competition among different RET types, deploying high-cost RETs, such as photovoltaics and fuel cell power, can be challenging. This may lead to a concentration on economically viable RETs. To address this issue, South Korea's RPS scheme sets a separate quota for photovoltaics, issuing distinct RECs for photovoltaic and non-photovoltaics RET-E. This results in different REC markets and prices for the two types of RET-E, ensuring a balanced deployment of photovoltaics[2]. To mitigate excessively different economic viabilities among RET types and to induce the deployment of environmentally friendly RET-E, a weighted REC allocation system (a multiplier system) has also been implemented.

[2] The separate REC market system for photovoltaics was abolished in 2016, after which the REC markets were unified.

3 Literature review

3.1 Comparison of the FIT and RPS schemes

There have been numerous empirical and theoretical comparative studies of the effectiveness and impact of FIT and RPS schemes. The FIT scheme, with its fixed tariff for the long-term purchase of RET-E, is recognized for creating a stable investment environment and, ultimately, deploying a larger amount of RET-E at a lower cost compared to the RPS scheme [15, 19-20]. The FIT scheme is considered advantageous for promoting immature RETs such as photovoltaics. However, there have been criticisms regarding government intervention in pricing RET-E and the yearly instability of the amount of RET-E deployment, as noted by Pyrgou et al. [21] and Hong et al. [4].

The RPS scheme is praised for enhancing cost reductions through competition among RETs and allowing for market-determined prices, thus providing basic flexibility in terms of pricing [13, 22]. García-Álvarez et al. [23] analysed the performance of the FIT and RPS schemes in promoting onshore wind power in the EU and concluded that only the FIT scheme and its design elements influence the installed capacity of onshore wind power.

Xin-gang et al. [24] analysed the FIT and RPS schemes in China from the perspective of achieving grid parity in RE, suggesting that under an FIT scheme, neither solar nor onshore wind power may reach grid parity, whereas under an RPS scheme, onshore wind power can achieve grid parity, but solar power may require additional subsidies. Yu et al. [25] examined the impact of RPS and FIT schemes on the interregional power transmission line layout in China and proposed that an increase in RPS targets may lead to an increase in the number of newly built lines, while the continuation of FIT subsidies beyond 2020 may decrease the level of demand for new line construction.

Research has also been conducted to analyse the performance of the FIT and RPS schemes in South Korea. Choi et al. [26] compared the outcomes of the FIT scheme implemented before 2011 with those of the ongoing RPS scheme since 2012 and concluded that from the government's perspective, the RPS scheme is more efficient for photovoltaic energy, while the FIT scheme is more efficient for non-photovoltaic RETs such as wind power. From the perspective of energy producers, the FIT scheme is more efficient for photovoltaic energy, but the RPS scheme is more efficient for non-photovoltaic RETs. Kwon [16] suggested that an improperly designed RE support system can provide excessive profits to RE operators. Kown [16] analysed South Korea's FIT and RPS systems, and noted that the

FIT scheme offers more rent for photovoltaic RET-E, while RPS provides more rent for non-photovoltaic RETs. Hong et al. [4] used a learning curve model to empirically analyse which scheme—FIT or RPS—is more effective in achieving grid parity for photovoltaics in South Korea, finding that in the RPS period, the LR for photovoltaics was 18.44%, while in the FIT period, it was negative (-0.28%), demonstrating the superiority of the RPS scheme in terms of achieving grid parity for photovoltaics.

The current research is closely related to Hong et al.'s research [4]. However, unlike Hong et al. [4], who focused on photovoltaics, the current research explores the impact of the FIT and RPS schemes on non-photovoltaic RETs, such as onshore wind power, bioenergy power, small hydropower, and fuel cell power.

Studies comparing the effects of FIT and RPS schemes on the promotion of RET industries also exist. Yi et al. [27] analysed the contributions of FIT and RPS schemes to the development of China's photovoltaic industry and concluded that the RPS scheme promotes long-term and rapid development more effectively than does the FIT scheme. Similarly, in the context of China's biomass industry, Yu-zhuo et al. [28] reported that compared with FIT, RPS contributes to faster long-term development. In addition to studies directly comparing the effectiveness of FIT and RPS schemes, studies have explored how the design elements of each system influence their effectiveness [29-30,23].

3.2 Learning curve effects for energy technologies

In the learning curve model, for each doubling of the total quantity of products produced, the average unit cost decreases by a fixed proportion, called the learning rate (LR). This concept is often used in economics and business to describe the relationship between learning or experience and performance or productivity.

Technological learning, or the learning effect, is generally classified into five types: learning-by-doing, learning-by-researching, learning-by-using, learning-by-interacting, and economies of scale [31-33]. Arrow [34] initially introduced learning-by-doing, referred to as the one-factor learning curve (1FLC) model, in which the LR is derived from cumulative capacity or production. In addition to the 1FLC model, a two-factor learning curve (2FLC) model that considers not only accumulated capacity but also accumulated research exists [35-36].

Many scholars have applied learning curve models to analyse energy technologies. Rubin et al. [37] analysed research results and calculated the LRs of 11 electricity supply technologies, including fossil fuel, nuclear, and RETs. They noted significant differences in

LRs among the same energy technologies across various research outcomes, suggesting the need for systematic studies when analysing policy effects. Moreover, studies that estimate the LRs for emerging technologies, such as carbon storage, batteries, electrolysis, and fuel cell electric vehicles, across different scenarios have been conducted [38-41]. These studies predicted future price reductions with increased production volumes.

Egli et al. [42] calculated LRs using data from photovoltaics and onshore wind projects in Germany, reporting LRs of 5% and 24%, respectively. They expressed sceptical opinions regarding the phasing out of policy support for such projects.

Hong et al. [35] derived the LR of photovoltaic generation in South Korea using the 1FLC and 2FLC models, empirically verifying the cost reduction effect of R&D investment. Kittner et al. [36] derived a stable solar power generation path with solar power at $1 per watt and battery storage at $100 per kWh using 2FLC model for energy storage batteries. Wei et al. [43] calculated the LRs of six energy-related technologies and argued that deployment programmes can alter the shape of the learning curve, inducing changes such as downwards bending, depending on the deployment programme utilized.

4 Methodology

The FIT-to-RPS transition represents a significant shift in the deployment programme for RET-E in South Korea. As described in Figure 4, the difference in the cumulative amount of RET-E generation under the FIT and RPS schemes leads to varying unit costs of RET-E generation under each scheme due to the learning curve effect (① in Figure 4). This learning curve effect is a natural outcome that occurs as the volume of deployment increases. On the other hand, the change in the LR is a consequence of the programme shifting from an FIT scheme to an RPS scheme (② in Figure 4). When assessing the effectiveness of a programme transition in terms of cost reduction for RET-E, attention should be focused on the shift of the LR, as indicated by ② in Figure 4.

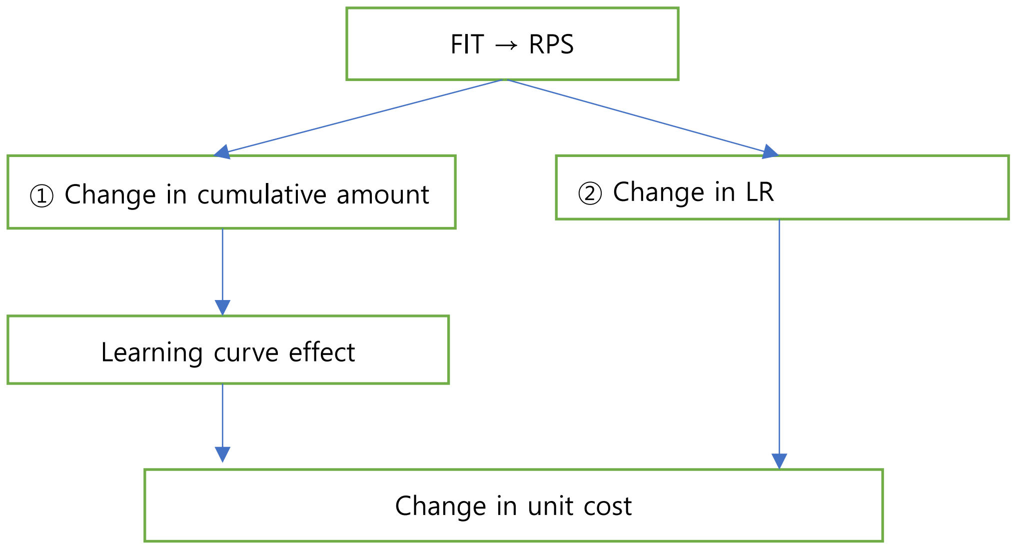


Figure 4 Two channels of the effect of the FIT-to-RPS transition on the decrease in the unit cost of RET-E generation (modified from Hong et al. [4])

This research focuses on how the LRs of four types of RETs, namely., onshore wind power, bioenergy power, small hydropower, and fuel cell power, changed after shifting from the FIT scheme to the RPS scheme in South Korea. A 1FLC model is employed to calculate the LR for each FIT and RPS scheme in this research.

Equation (1) provides a description of the 1FLC model:

$$UC_t = C_0 \cdot (CUM_t)^a \quad (1)$$

Let us consider onshore wind power generation. UC_t represents the unit cost of generating onshore wind power, C_0 denotes the initial cost of onshore wind power generation, and CUM_t indicates the cumulative amount of onshore wind power generation. While the learning curve model requires the use of cumulative installed capacity data of onshore wind power as an explanatory variable, cumulative generation data are used in this research. This is because the focus of this research is on generation rather than installed capacity, and obtaining quarterly data on the installed onshore wind power capacity is very challenging in practice. Many studies have also chosen to use cumulative power generation as the explanatory variable when estimating the LR of RETs. [44-49,35,4]. In this work, t is the given time, and a is the learning index related to the progression rate (PR) and LR:

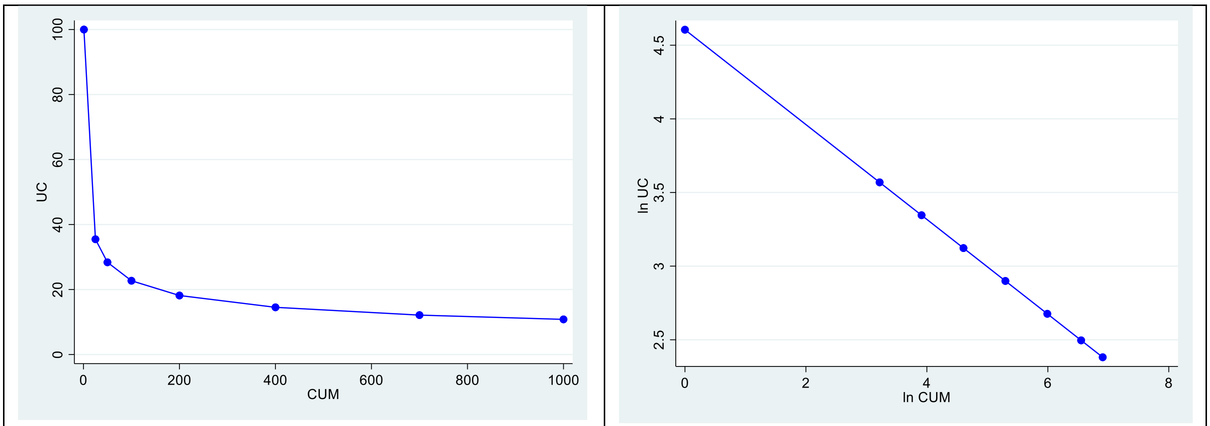
$$PR = 2^a \quad (2)$$

$$LR = 1 - PR = 1 - 2^{a} \quad (3)$$

PR and LR represent the change and reduction in unit cost, respectively, when cumulative onshore wind power generation doubles.[3] To calculate 'a', Equation (1) is transformed into a logarithmic scale, resulting in Equation (4), which is a linear function, as illustrated in Figure 5:

$$\ln UC_t = \ln C_0 + a \cdot \ln CUM_t \quad (4)$$

With empirical data for UC_t and CUM_t, 'a' in Equation (4) can be obtained through regression analysis.



(a) Linear scale learning curve from Equation (1)

(b) Log-log scale learning curve from Equation (4)

Figure 5 Examples of learning curves (modified from Kahouli-Brahmi [32])

[3] For instance, if the PR is 0.8, then the unit cost decreases to 80% when the amount of cumulative onshore wind power generation doubles. Similarly, with an LR of 0.2, or 20%, the unit cost decreases by 20% when the amount of cumulative generation is doubled.

5 Data

5.1 Period and RETs of analysis

The data analysis period spans from 2002 to 2020, during which the FIT scheme was implemented from 2002 to 2011, and the RPS scheme has been in place since 2012. To employ regression analysis for calculating the LR, more than 30 samples are needed in each scheme to ensure statistical significance. The amount of annual data available in each scheme is insufficient for ensuring statistical significance. Consequently, quarterly data rather than annual data are used for modelling. The analysed RETs are onshore wind power, bioenergy power, small hydropower, and fuel cell power[4].

5.2 Amount of RET generation during the FIT and RPS scheme periods

The data for this learning curve model are obtained from the KNREC and the Korea Power Exchange (KPX), which have authority over the deployment and management of RET-E in South Korea. The detailed description of the amount of RET generation is in Appendix B.

5.3 Unit price of RET-E generation during the FIT and RPS scheme periods

[4] In fact, fuel cell power is not a type of RET. Moreover, in South Korea, it is classified under the category of 'new energy technology'. Through the FIT and RPS schemes, new energy technologies, such as fuel cell power, have also been receiving support.

The most accurate variable for measuring the LR is the production unit cost. However, obtaining the production unit cost is challenging because it is closely associated with a company's operational strategy. Therefore, in this research, as in other studies, unit price, which is easier to obtain than unit cost, is used instead [4,35,44-48,50].

To derive the unit price, transaction cost data for RET-E are obtained from the KNREC and KPX. To account for the deflation effect over time, the data for each year are adjusted using the gross domestic product (GDP) deflator (2015=100) from the Korean Statistical Information Service (KOSIS). The quarterly data regarding the deflation-adjusted transaction costs of RET-Es, along with the cumulative data, are detailed in Appendix C.

From the cumulative amount of RET-E in Figure B (b) and the cumulative transaction cost of RET-E in Figure C (b), we can calculate the unit cost[5].

Consequently, we can generate a plot of the unit cost versus cumulative power generation, as shown in Figure 6 and a log-log scale learning curve plot of the cumulative amount of RET-E generation versus unit cost, as shown in Figure 7.

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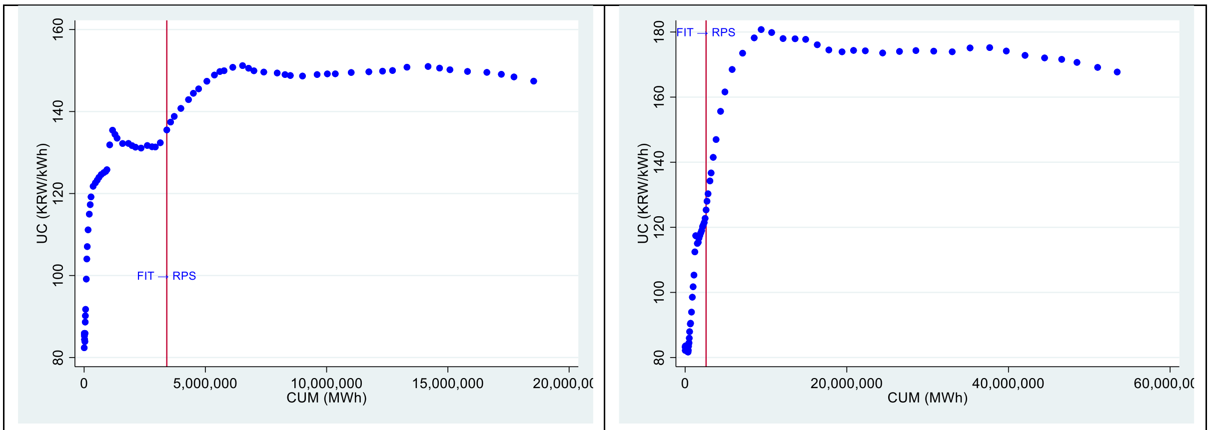
[5] Strictly speaking, this is the unit price. However, in this study, we calculate and use the unit price as a substitute for unit cost, and thus, we continue to use the term 'unit cost'.



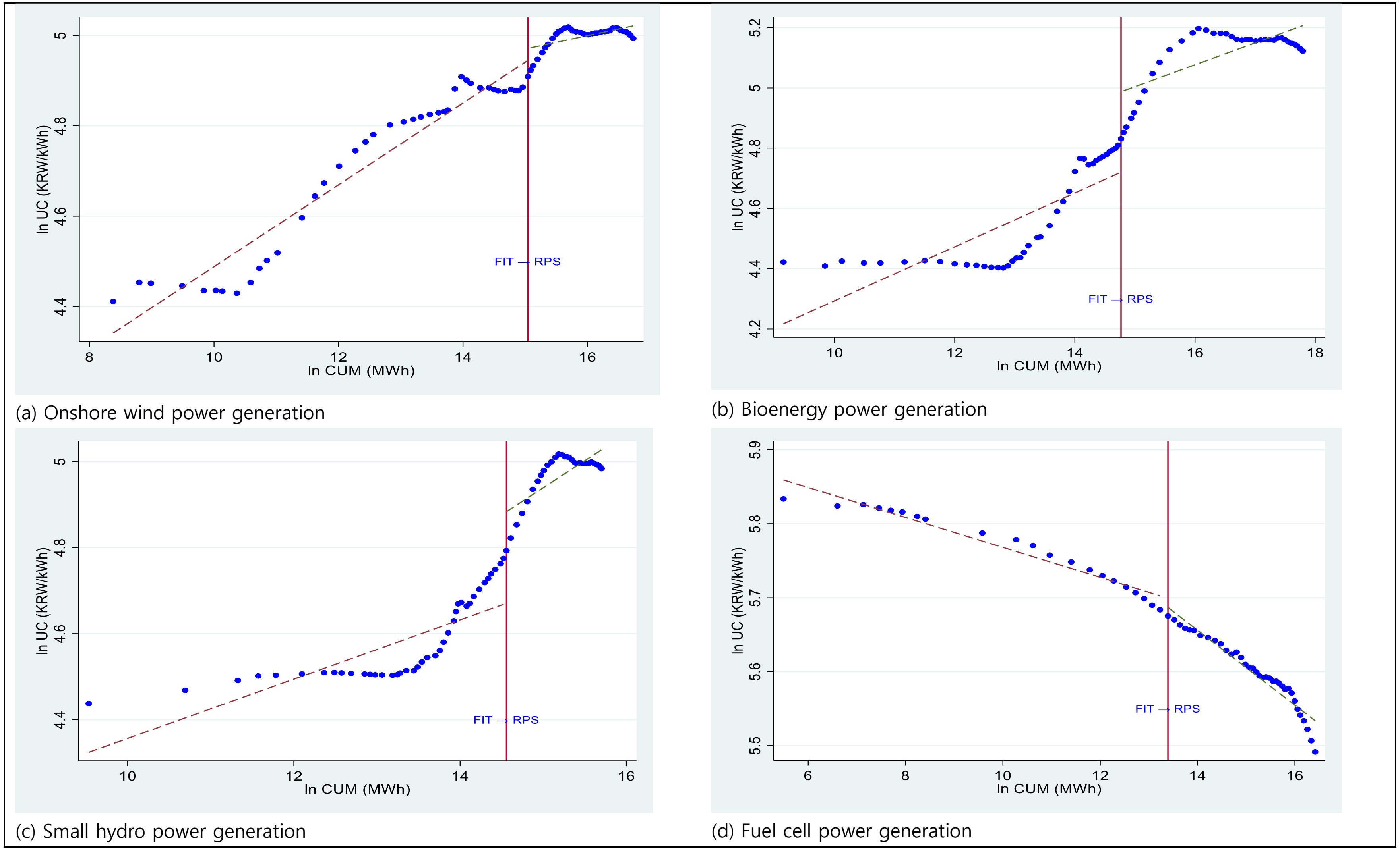
(a) Onshore wind power generation

(b) Bioenergy power generation

(c) Small hydro power generation

(d) Fuel cell power generation

Figure 6 Unit cost versus cumulative power generation



(a) Onshore wind power generation

(b) Bioenergy power generation

(c) Small hydro power generation

(d) Fuel cell power generation

Figure 7 Learning curves for the FIT and RPS scheme periods on a log-log scale

6 Results and discussion

In Figure 7, onshore wind power, bioenergy power, and small hydropower exhibit similar curve shapes. However, fuel cell power displays a significantly different pattern from those of the other three RETs. The learning curve shapes for onshore wind power, bioenergy power, and small hydropower do not exhibit a linear pattern, and the estimated regression lines display positive slope values, indicating negative LRs. Despite the increase in cumulative generation, these three RETs do not exhibit a clear learning effect of a decrease in the unit cost. Instead, the unit costs show trends of increasing or remaining stable.

Figure 7 displays the log-log scale learning curves for the four RETs, and the estimated LRs for the FIT and RPS scheme periods are presented in Table 1.

According to Table 1, regardless of the FIT-to-RPS transition, onshore wind power, bioenergy power, and small hydropower have negative LRs. Additionally, the adjusted R^2 values of the estimated regression equations for onshore wind power, bioenergy power, and small hydropower, except for the FIT period for onshore wind power (0.930), are less than 0.7, indicating relatively weak explanatory power.

RET	Period	Estimated regression equation	Adjusted R^2	LR
Onshore wind power	FIT	$\ln UC_t = 3.583^{***} + 0.091^{***} \cdot \ln CUM_t$	0.930	-6.5%
	RPS	$\ln UC_t = 4.528^{***} + 0.029^{***} \cdot \ln CUM_t$	0.380	-2.0%
Bioenergy power	FIT	$\ln UC_t = 3.398^{***} + 0.090^{***} \cdot \ln CUM_t$	0.626	-6.4%
	RPS	$\ln UC_t = 3.916^{***} + 0.073^{***} \cdot \ln CUM_t$	0.510	-5.2%
Small hydro power	FIT	$\ln UC_t = 3.668^{***} + 0.069^{***} \cdot \ln CUM_t$	0.607	-4.9%
	RPS	$\ln UC_t = 3.053^{***} + 0.126^{***} \cdot \ln CUM_t$	0.576	-9.1%
Fuel cell power	FIT	$\ln UC_t = 5.970^{***} - 0.020^{***} \cdot \ln CUM_t$	0.949	1.4%
	RPS	$\ln UC_t = 6.365^{***} - 0.051^{***} \cdot \ln CUM_t$	0.924	3.5%

Table 1 Estimated LRs (note: *** p value<0.01)

However, fuel cell power has a comparatively greater adjusted R^2 in the estimated regression equation, surpassing 0.9 for both the FIT and RPS scheme periods. Additionally, fuel cell power exhibits positive LRs under both the FIT and RPS schemes, with the LR under the RPS scheme (i.e., 3.5%) being greater than that under the FIT scheme (i.e., 1.4%), which implies that the transition to the RPS regime resulted in an improved learning effect.[6] To verify the robustness of the outcomes reported in Table 1, a 2FLC model was implemented. The learning-by-doing rates derived from the 2FLC model were similar to

[6] To determine whether there is a structural break in the learning curve between the FIT and RPS periods, a Chow test was conducted for the four RETs. The results of the Chow test indicated that there is a structural break between FIT and RPS periods for all the four RETs, with a confidence level of 1%.

those obtained from the above 1FLC model. [7]

Hong et al. [4] analysed the impact of transitioning from the FIT scheme to the RPS scheme on the learning curve of photovoltaics, as shown in Figure 8. According to Hong et al. [4], the FIT-to-RPS transition resulted in a significant change in the learning curve for photovoltaics, with the LR shifting from -0.28% to 18.44%. Comparing the analysis results of the four RETs analysed in this paper with the analysis conducted by Hong et al. [4] for photovoltaics, it is evident that among the four RETs, only the trend for fuel cell power is shown to be similar to that for photovoltaics. Hong et al. [4] argued that the RPS scheme effectively facilitated cost reductions through promoting competition among RETs via the REC market. They observed that this mechanism works well for photovoltaics. However, in the current study, this learning effect mechanism was effective only for fuel cell power among the four non-photovoltaic RETs. For the other three RETs, namely, onshore wind power, bioenergy power, and small hydropower, such mechanisms and cost reductions are not clearly observed.

[7] A detailed description and the results of the 2 FLC model are provided in Appendix A.

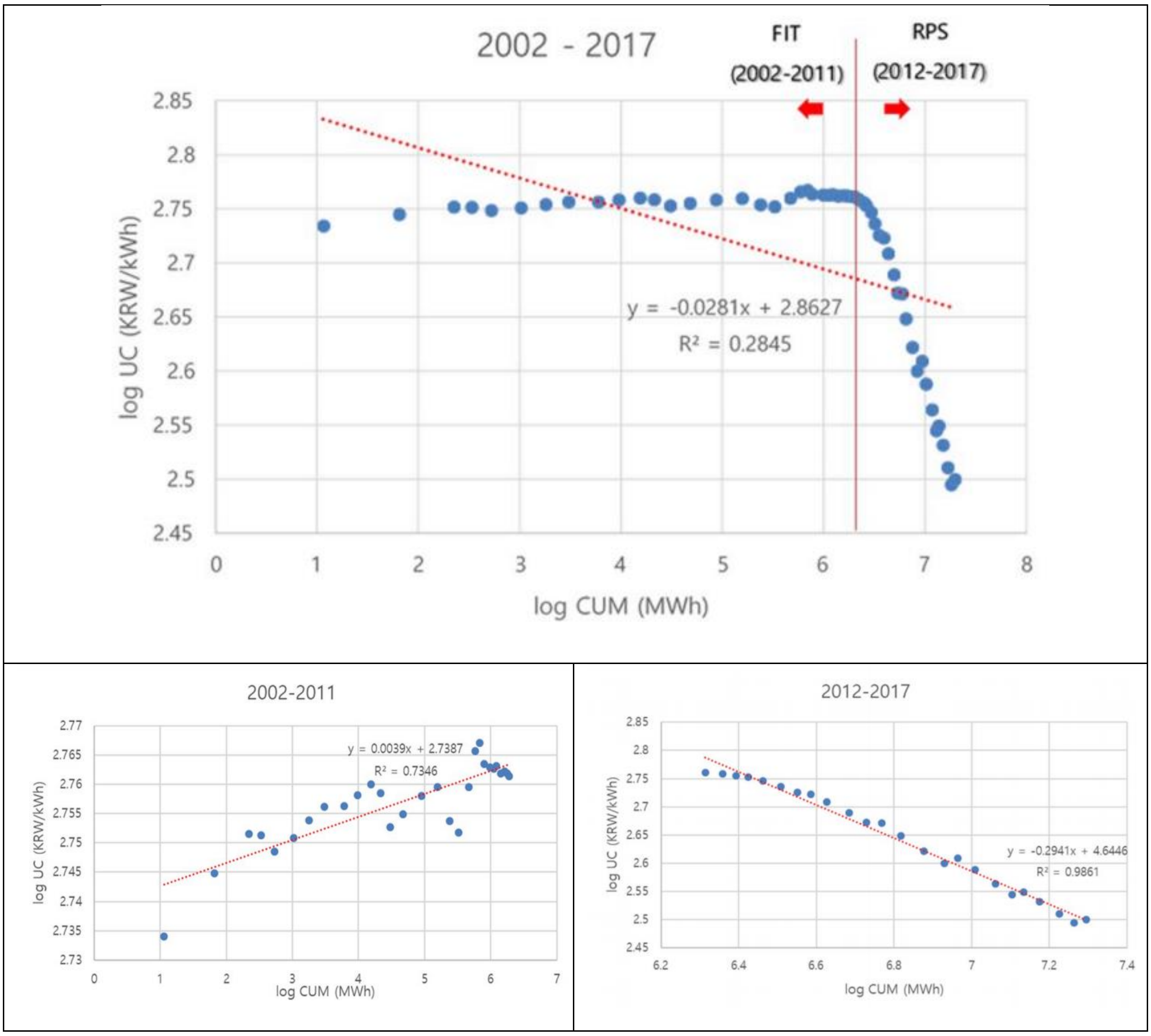


Figure 8 Learning curve of photovoltaics during the FIT and RPS scheme periods (Hong et al. [4])

When the RE support scheme transitioned from the FIT to the RPS, among the four RETs, fuel cell power demonstrated a more apparent learning effect. In contrast, for onshore wind power, bioenergy power, and small hydropower, the learning effect was not realized in both the FIT and RPS periods. In the case of small hydropower, the negative LR became worse in the RPS period than in the FIT period.

This finding can be explained by the following two factors.

The first reason is related to site constraints and land availability restrictions in South Korea[8]. Initially, RE power plants were installed at sites with favourable wind conditions or ideal conditions for small hydropower and bioenergy power. Subsequently, as favourable sites were exhausted, RE power plants were installed at less favourable sites. Consequently, the increased cost incurred by installing on these unfavourable sites offset the cost reduction effect resulting from the increase in the amount of cumulative production. In contrast, photovoltaics and fuel cell power systems were relatively less affected by site limitations. Solar energy is evenly distributed in South Korea, and thus, the cost of photovoltaic generation is significantly influenced by improvements in photovoltaic performance. In South Korea, fuel cell power commonly utilizes processed natural gas as fuel, providing a stable supply without increasing fuel prices. Hence, the generation cost of fuel cell power is influenced mainly by the performance and efficiency of fuel cell devices.

The previous explanation can be described through the concept of the levelized cost of electricity (LCOE). LCOE represents the average lifetime cost of generating electricity for a generator [51]. LCOE for RE generation largely depends on four factors: installed cost,

[8] South Korea is a relatively small country, covering an area of 100,413 km^2, with 70% of its territory being mountainous.

capacity factors, operation and maintenance costs, and the weighted average cost of capital (WACC) [52]. Installed costs are determined by equipment costs, construction work, grid connections, planning and project costs, and land, i.e., site-specific characteristics. Capacity factors represent the percentage of time a power plant operates at maximum output over a 24-hour period. For example, the capacity factor for wind power generation is influenced by the nature and quality of wind resources and the technology applied such as the design and operational availability of wind turbines. LCOE will vary depending on the installed cost and the capacity factor for a particular installation and location [53]. As more wind power plants are installed, technological innovations and learning effects lead to increase turbine capacity, blade length, etc., which decrease installed costs and increase capacity factors. However, as suitable locations become scarce and developers are forced to use less optimal, more expensive sites, the installed costs rise and capacity factors diminish. If the detrimental effects of these less favourable locations outweigh the benefits of technological advancements, the LCOE will increase.

This phenomenon also applies to small hydropower, for which increasingly challenging sites lead to higher development costs, more complex engineering conditions and lower capacity factors, thus increasing the LCOE. Similarly, the expansion of bioenergy power, which involves fuel costs, can lead to competition for fuel for other uses such as agriculture, pushing up the LCOE as fuel becomes a scarce resource [52,53].

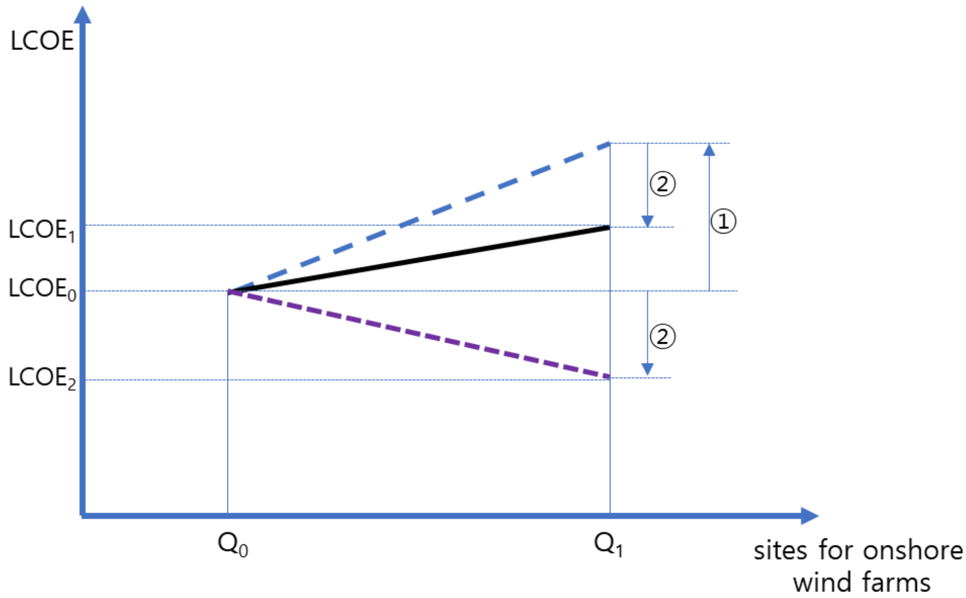


Figure 9 Impact of an increase of onshore wind farm sites on LCOE

Figure 9 illustrates the corresponding results for onshore wind power. As the onshore wind farms expand from Q_0 to Q_1, installing wind farms at sites with higher installed costs and poorer wind quality causes the LCOE to increase by ①. In contrast, technological innovations such as increased turbine capacity and the effects of scale economy lead to a decrease in LCOE by ②, partially offsetting the increase represented by ①. If the magnitude of ① exceeds that of ②, the LCOE will ultimately increase from $LCOE_0$ to $LCOE_1$. If the issue of depleting favourable sites would not have occurred, the LCOE would have decreased from $LCOE_0$ to $LCOE_2$.

The second reason is related to the cost reimbursement structure of the FIT and RPS schemes. Under the FIT scheme, the government establishes standard prices for each RET and purchases RET-E at these standard prices for 15 years. Hence, RE power plant operators receive revenue equivalent to the standard price. These standard prices are periodically adjusted and announced by the government based on technological advancements or policy objectives. Lowering the standard price makes it much closer to the electricity market price, i.e., the system marginal price (SMP). The SMP fluctuates depending on the electricity market conditions. In situations where the SMP suddenly increases due to certain market circumstances, there are cases in which the standard price temporarily becomes lower than the SMP (Figure 2).

In contrast, the RPS scheme enables RE power plant operators to earn revenue equal to "SMP + REC". When generating RET-E, RE power plants sell electricity to the electricity market and earn revenue equivalent to the SMP, while the RECs[9] obtained from RET-E generation are sold in the REC market to generate additional revenue (Figure 3). Therefore,

[9] REC issuance quantities are determined differently based on the type of RETs and even within the same RET category, which is referred to as a multiplier. For instance, for 1 megawatt-hour (MWh) of electricity generation, onshore wind power receives 1 REC, small hydropower receives 1.5 RECs, and fuel cell power receives 2 RECs.

RE power plants always earn an income higher than the SMP by the price of RECs.

Hence, although the RPS scheme may encourage cost reductions through competition, when the difference between the standard price for the RET and the SMP is not significant, the FIT scheme may lead to greater cost reductions than the RPS scheme. The standard prices of onshore wind power, bioenergy power, and small hydropower were not significantly higher than SMPs, as shown in Figure 2.

7 Conclusions and policy implications

In this study, the impact of transitioning South Korea's RE support system from a price-based system (FIT) to a quantity-based system (RPS) on the cost reduction of non-photovoltaic RETs, namely, onshore wind power, bioenergy power, small hydropower, and fuel cell power, is analysed using a learning curve model. In the case of fuel cell power, an increase in the LR has accelerated the decrease in generation costs.

However, for onshore wind power, bioenergy power, and small hydropower, an evident improvement in the learning effect was not observed. The reasons for this are twofold. First, due to site constraints and limited land availability, as more RE power plants were installed, the availability of favourable sites decreased. This necessitated the installation of

RE power plants in areas that are less economically viable. Second, the RPS scheme, in which the generation cost is set as SMP + REC, possesses structural characteristics that make it challenging to decrease the cost to a level similar to SMP.

From this analysis, the following two policy implications can be drawn.

First, identifying and allocating competitive and attractive locations or lands for RE power generation is an important policy goal. For onshore wind power, bioenergy power, and small hydropower, policy measures aimed at improving irrational regulations and process burdens related to the installation of RE power plants, allowing for the installation of RE power plants under more favourable site conditions, may become very effective for reducing generation costs. One of the significant obstacles to the expansion of RE power plants lies in excessive and intricate regulations and procedures. Thus, strengthening policy efforts to simplify and eliminate such regulations and procedures is necessary to enable the installation of RE power plants at sites with good economic viability.

McKinsey & Company [54] noted that the expansion of renewable energy is critical not only for addressing climate change but also because dependency on fossil fuels, as seen in the Russia-Ukraine war, greatly weakens energy security. It is argued that finding adequate lands or sites will be a very challenging issue for expanding RE deployment in the future. Notably, the availability of land suitable for RE is constrained by technical, regulatory, and environmental limitations. For example, in the case of onshore wind power, excessive regulation is the most significant obstacle affecting land availability. Several alternatives are suggested to potentially increase land availability for RE, such as encouraging social acceptance, revisiting regulatory rules, fostering hybrid land use, and maximizing repowering.

A study on the barriers to RE deployment in Korea [55] identified unnecessary and irrational regulations as the most significant obstacles to the expansion of RE deployment in Korea. For example, even within regions that are not significantly different, there are frequent instances in which the distance requirements between RE power plants vary greatly among basic local governments. Particularly in the case of wind farms, Yeongdong County and Okcheon County have set minimum separation distances ranging from 500 metre to 1000 metre. Given the numerous existing legal restrictions on the location of RETs, the study highlights the need to remove unnecessary regulations, such as redundant rules, and to streamline related administrative procedures to promote efficient RE projects. Additionally, it is important to actively involve citizens in RE initiatives and provide related education to motivate them to support RE deployment.

The second implication is related to improving the RPS scheme, possibly by adopting a system similar to the hydrogen power auction market system (i.e., the Clean Hydrogen Portfolio Standard (CHPS)) established in 2023 in South Korea. The hydrogen power auction market system is a government-regulated system in which the government announces the annual hydrogen power purchase volume, opens an auction market for hydrogen power generation, and awards contracts for environmentally and economically viable hydrogen power generation to ensure long-term supply at a fixed generation price. This system involves a long-term fixed hydrogen power price that is not divided by the SMP or REC, making it advantageous for inducing cost reductions.

Meanwhile, this study has the following limitations, so the research results need to be interpreted with caution. First, due to data collection constraints, unit price was used instead of unit cost and the more comprehensive 2FLC[10] methodology was not employed in the learning curve model. Furthermore, due to the limitations of the 1FLC model, some important variables, such as raw material prices, which could be correlated with other

[10] In Appendix A, the results of the 2FLC analysis have been added to validate the robustness of the 1FLC model analysis. However, due to data collection constraints, only the knowledge stock from the government sector was included, whereas that of the private sector was not, which also represents a limitation

explanatory variables may have been omitted. These factors raise concerns about potential estimation bias in the analysis results. Second, this study pertains to South Korea, which has a small land area with mountains covering 70%, thus resulting in limitations in land availability. In countries with large land area where there are no land constraints related to the installation of RE power plants, the learning effect may become evident as RE power generation increases, leading to significant cost reductions. Therefore, it is problematic to generally apply these findings to countries with fewer land constraints. What this study implies is that in countries like South Korea, where the land area is small and land availability limitations are severe, cost reductions in RE generation may not be clearly realized even if RE generation accumulates. Therefore, policy efforts to improve land availability are necessary.

Future research could involve quantitatively assessing the cost increases associated with land availability limitations in countries where these limitations are severe for various RE sources. This would be significant both politically and academically, aligning with the trend towards expanding the installation of RE power plants.

APPENDIX A. The results of two-factor learning curve (2FLC) analysis

While the 1FLC model relies only on the effects of learning-by-doing, considering only installed capacity or production, the 2FLC model also accounts for the effects of learning-by-researching, which originates from knowledge stock through the accumulation of R&D investment, in addition to learning-by-doing.

Therefore, the 2FLC model is generally expressed as follows:

$$UC_t = C_0 \cdot (CUM_t)^a \cdot (KS_t)^b \qquad \text{(A-1)}$$

$$KS_t = (1-\rho) \cdot KS_{t-1} + RD_{t-RDlag} \qquad \text{(A-2)}$$

By taking the logarithmic form of equation (A-1), the following equation is obtained:

$$\ln UC_t = \ln C_0 + a \cdot \ln CUM_t + b \cdot \ln KS_t \qquad \text{(A-3)}$$

In the above equations, KS represents the knowledge stock and is calculated as shown in equation (A-2). According to equation (A-2), the knowledge stock depreciates annually by ρ, and R&D investment contributes to the knowledge stock after a time lag of $RDlag$. In equation (A-1), a represents the learning-by-doing index (LDI), and b represents the learning-by-researching index (LRI), and the learning-by-doing rate (LDR) and the learning-by-researching rate (LSR) are as follows:

$$LDR = 1 - 2^{a}, \quad LSR = 1 - 2^{b}$$

Figure A-1 shows the annual and cumulative government R&D investments for the four RETs from 2002 to 2020.

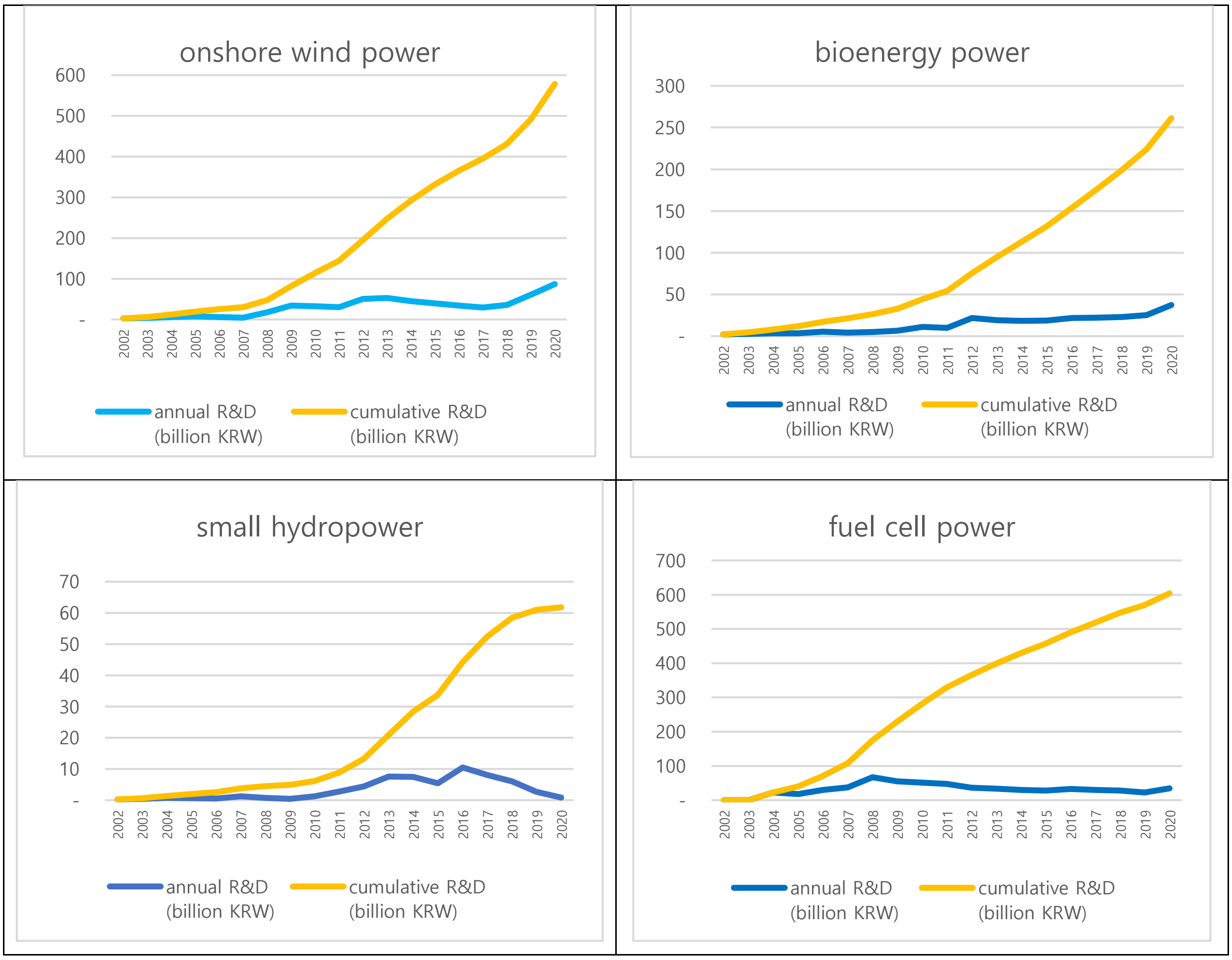


Figure A-1 Annual and cumulative government R&D for RETs (source: IEA, Energy Technology RD&D Budgets)

To calculate the quarterly government R&D budget, the annual government R&D investment was assumed to be allocated quarterly at 30%, 30%, 20%, and 20%

respectively.[11] The GDP deflator (2015=100) was also used to compute the quarterly knowledge stock.

In the 2FLC model, various time lags and depreciation factors can be applied. Referring to Hong et al. [35], who applied the 2FLC model to Korea's photovoltaics, $RDlag$=3 and ρ=0.2 are assumed in the current 2FLC model. The results of the 2FLC with quarterly knowledge stock are shown in Table A-1.

RET	Period	CUM		KS		Adjusted R^2	DW	VIF
		LDI	LDR	LRI	LSR			
Onshore wind power	FIT	0.130***	-9.4%	-0.060***	4.1%	0.948	0.20	8.31
	RPS	0.037***	-2.6%	0.055***	-3.9%	0.563	0.14	1.01
Bioenergy power	FIT	0.306***	-23.6%	-0.362***	22.2%	0.829	0.40	18.75
	RPS	0.019	-1.3%	0.340***	-26.6%	0.719	0.23	3.04
Small hydro power	FIT	0.206***	-15.3%	-0.132***	8.7%	0.861	0.47	5.53
	RPS	0.048***	-3.4%	0.088***	-6.3%	0.829	0.19	1.94
Fuel cell power	FIT	-0.030***	2.1%	0.079***	-5.6%	0.983	0.74	8.31
	RPS	-0.057***	3.9%	-0.026	1.8%	0.927	0.15	24.78

Table A-1 Results of the 2FLC model analysis

As shown in Table A-1, similar to the results of the 1FLC model analysis, for onshore wind power, bioenergy power, and small hydropower, the LDRs are negative during both the FIT

[11] Because the Korean government encourages spending more than 60% of the annual budget in the first half of the year to stimulate the domestic economy, it is reasonable to allocate such proportions on a quarterly basis [35].

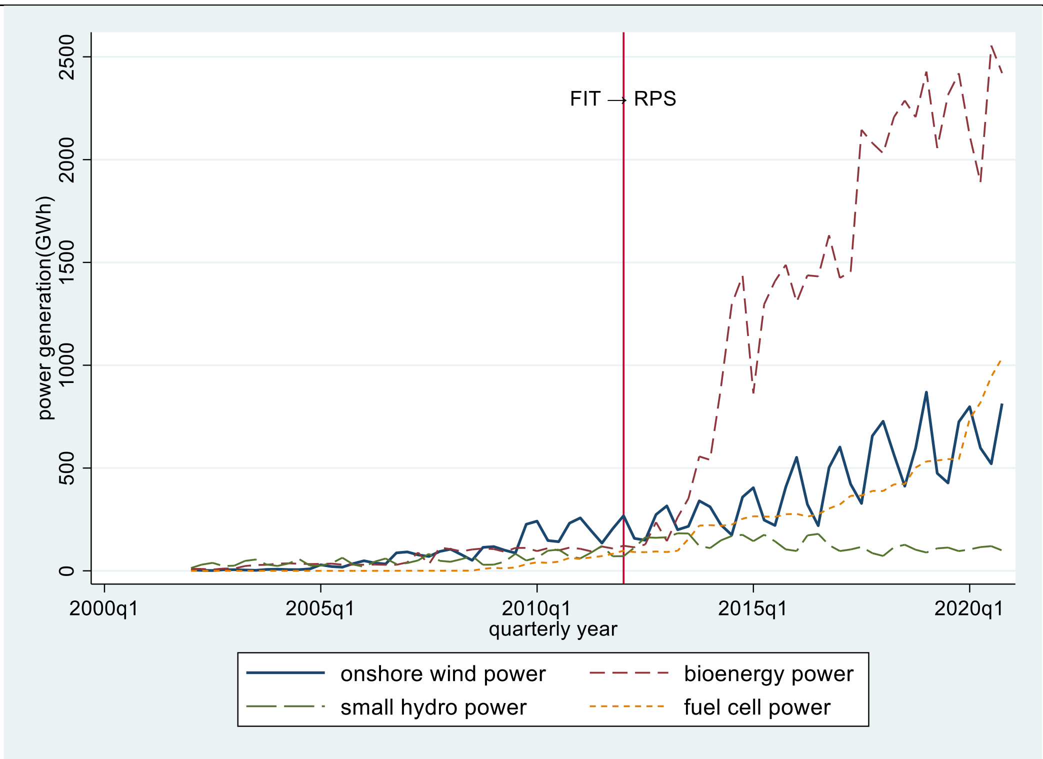
and RPS periods. This indicates that despite the accumulation of production, a positive learning-by-doing effect is observed for neither the FIT nor the RPS schemes. On the other hand, fuel cell power displays a positive learning-by-doing effect during the FIT period, and this effect increased during the RPS period.

The learning-by-researching effect for onshore wind power, bioenergy power, and small hydropower is positive during the FIT period and negative during the RPS period. In contrast, the learning-by-researching effect for fuel cell power is negative during the FIT period and positive during the RPS period. However, interpreting the analysis results of the learning-by-researching effect requires great caution. To accurately calculate the knowledge stock, it is necessary to consider both government and private sector R&D investments to reflect the total national R&D investment in the model. Nonetheless, in this analysis, due to the practical difficulty of obtaining data for private sector R&D investments, only the government's R&D investment was included. Because the private sector is growing larger than the public sector in the Korean economy, the omission of private sector R&D investment may be a significant limitation of this 2 FLC model. This limitation may have distorted not only the analysis results of learning-by-researching but also those of learning-by-doing. In conclusion, the analysis results of the 2FLC model reveal that effects of learning-by-doing during the FIT and RPS periods are similar to those in the 1FLC analysis. However, it is important to exercise caution when interpreting the results of the 2FLC model analysis.

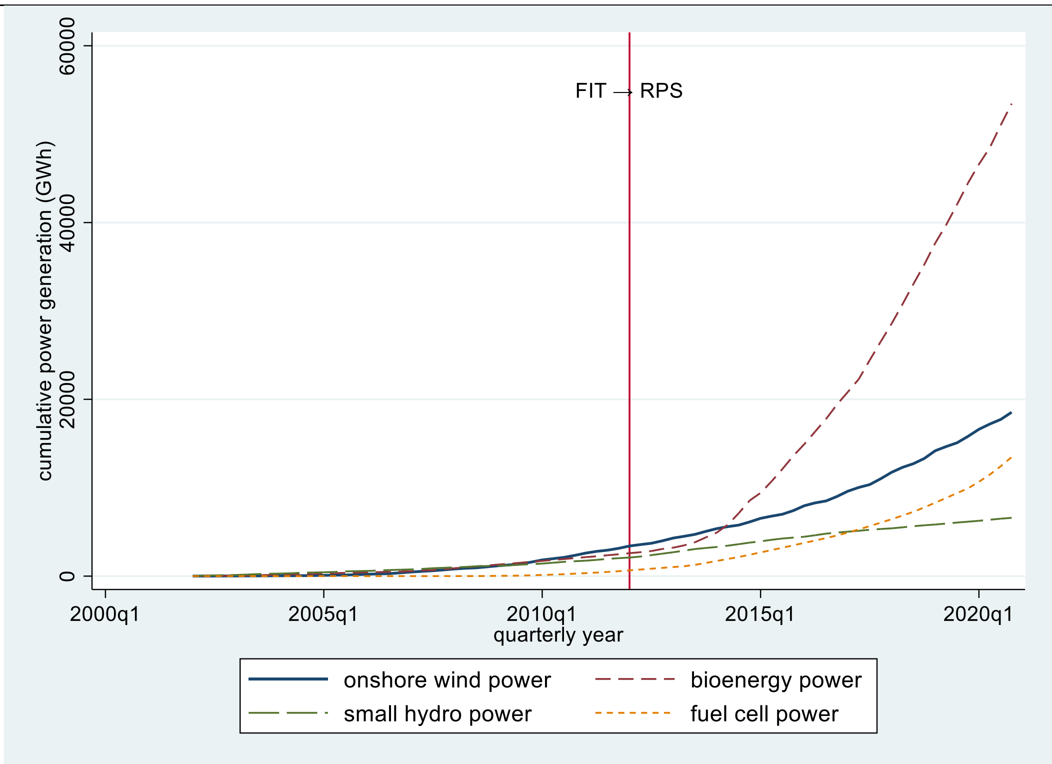
APPENDIX B Amount of RET generation during the FIT and RPS scheme periods

Figure B-1 displays the quarterly and cumulative amounts of RET-E generated under the FIT and RPS schemes from 2002 to 2020. Figure B-1 (a) shows the quarterly generation from installed RE power plants under the FIT scheme through 2011. Since 2012, indicated by the red vertical line, the RPS scheme has been implemented, and subsequent RE power plants have been installed under the RPS regime. Additionally, under the RPS scheme, RET-E generation continues at RE power plants that were initially installed under the FIT scheme. Therefore, the quarterly generation since 2012 comprises the amount generated from operational RE power plants installed under the FIT scheme before 2012 and that of newly installed RE power plants operating under the RPS regime. These quarterly data shown in Figure B-1 (a) are combined to establish the cumulative plot in Figure B-1 (b). Figure B-1

(a) shows that under the FIT regime, the amount of quarterly generation of the four RETs did not significantly increase. However, since the implementation of the RPS scheme in 2012, substantial increases have been observed in the amounts of bioenergy power generation, fuel cell power generation, and onshore wind power generation. This trend is also reflected in the cumulative generation data shown in Figure 6 (b), which suggests that the RPS scheme made a greater contribution to the increase in the three types of RET-E generation than did the FIT regime.



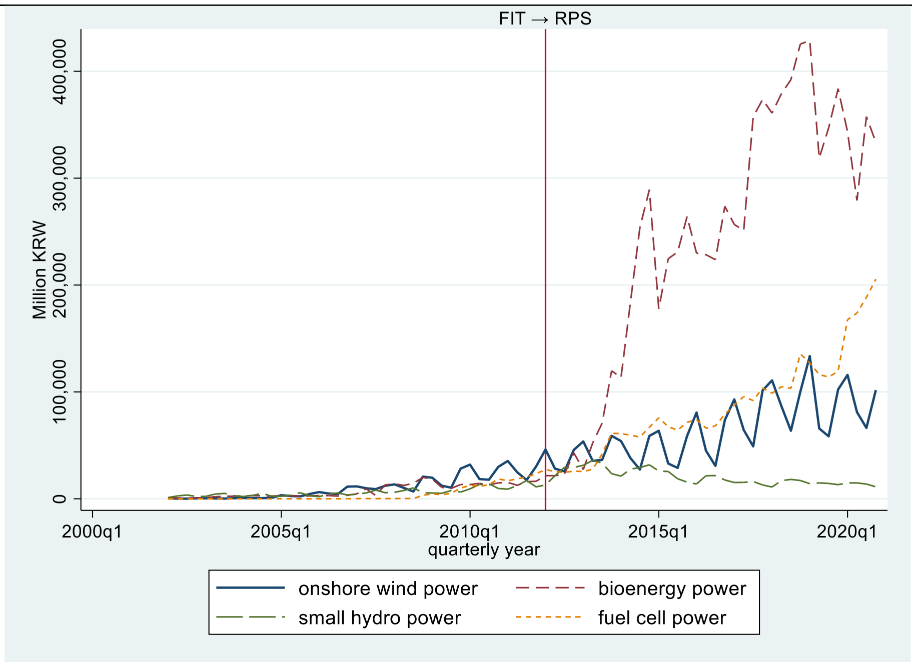
(a) Quarterly power generation under the FIT and RPS schemes (source: KNREC, KPX)



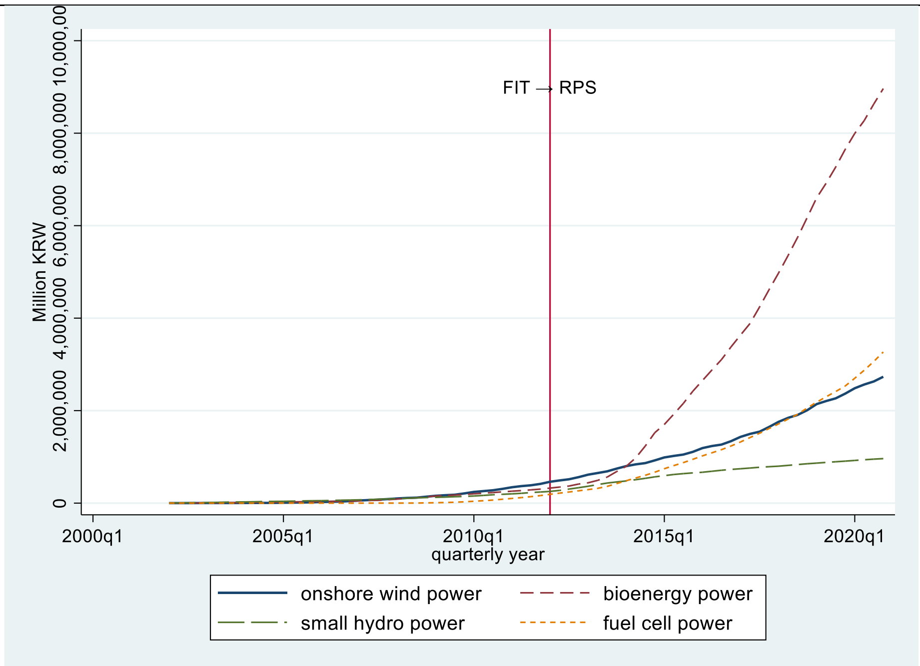
(b) Cumulative power generation under the FIT and RPS schemes (source: KNREC, KPX)

Figure B-1 Quarterly and cumulative power generation from RETs

APPENDIX C Quarterly and cumulative transaction costs of RETs



(a) Quarterly transaction cost of RETs



(b) Cumulative transaction cost of RETs

Figure C-1 Quarterly and cumulative transaction costs of RETs

* Under the RPS scheme, accurately calculating transaction costs requires knowledge of real-time REC prices and which RECs were used for settlement. However, since this is not feasible, monthly average prices were calculated and applied instead.

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(Chapter 2) Comparing Reduced Form VAR and Structural VAR in Analysing Causal Relationships Between Economic Growth, Energy Mix, and CO2 Emissions

1 Introduction

Environmental issues, including CO2 emissions, and economic growth are critical policy targets for all countries. Energy significantly impacts both economic growth and environmental concerns. These three factors influence each other, making their analysis a major focus for researchers. Numerous studies have examined these relationships using time series analyses across different countries. For instance, the relationship between economic growth and environmental issues has frequently been explored through the environmental Kuznets curve hypothesis (Luzzati and Orsini, 2009; Shahbaz et al., 2013; Özokcu and Özdemir, 2017; Awaworyi Churchill et al., 2018). Similarly, the relationship between energy use and environmental issues has been widely studied, focusing on how renewable, nuclear, and fossil fuel energy sources impact CO2 emissions (Belaïd and Zrelli, 2019; Begum et al., 2015; Saidi and Omri, 2020; Sadorsky, 2009; Dogan and Seker, 2016; Balsalobre-Lorente et al., 2018).

Dynamic models, such as the Vector Autoregressive (VAR) model, have been extensively used to analyze these relationships. The traditional and standard VAR model, also known as the reduced form VAR model is widely used in empirical research due to its simplicity, flexibility, and ease of implementation. It does not require theoretical restrictions, making it accessible for exploring dynamic interactions based purely on observed data. It is valued for its data-driven approach and ability to provide insights through tools like impulse response functions and Granger causality test result. These features make it an ideal preliminary tool for examining relationships, establishing robustness, and serving as a foundation before applying more complex models like structural VAR. However, it does not account for immediate effects between variables, which are particularly relevant in the energy and environmental sectors where changes often occur contemporaneously. For example, an increase in fossil fuel usage leads to an immediate rise in CO2 emissions. As a result, relying solely on the reduced-form VAR model can lead to significant limitations in analyzing energy policy impacts, potentially misrepresenting causal relationships.

In contrast, the Structural VAR (SVAR) model, introduced by Sims (1980), incorporates contemporaneous effects [12] by imposing theoretical restrictions, enabling causal interpretation of shocks. These features make SVAR a more robust tool for evaluating

[12] In the context of the SVAR model, contemporaneous effects refer to the immediate interactions between variables within the same time period. This concept highlights the SVAR model's ability to capture direct causal relationships, providing a key advantage over traditional VAR models. The time unit is crucial when considering lagged effects. If the time unit is a day or a month, the energy mix may be assumed to have only a lagged effect on CO2 emissions. However, when the time unit is a year, what appears as a lagged effect in shorter time units becomes a contemporaneous effect. Therefore, the choice of time unit can make the effect seem either lagged or contemporaneous.

complex relationships, such as those in energy and environmental systems. Additionally, by addressing immediate interactions among variables, SVAR allows for a more nuanced and realistic evaluation of policy impacts, particularly in sectors where contemporaneous effects are critical.

Despite its advantages, there is limited empirical research comparing the results of reduced-form VAR with those of SVAR, particularly regarding their implications for energy policy. This study bridges this gap by comparing these models to better understand how assumptions within each influence findings. While reduced-form VAR offers flexibility and simplicity, SVAR provides deeper insights by addressing the dynamic and immediate interactions that shape energy policy outcomes.

This study analyzes empirical data from South Korea and Japan, focusing on the causal relationships between the energy mix, economic growth, and CO_2 emissions. South Korea and Japan are highly relevant case studies for this research due to their shared challenges and distinct approaches to energy policy and structure. As resource-poor nations heavily dependent on energy imports, both face significant energy security concerns but have developed unique strategies to address these issues. South Korea has made substantial strides in integrating nuclear power to reduce reliance on fossil fuel imports and enhance energy self-sufficiency. Its long-standing reliance on nuclear energy, combined with recent shifts toward renewables under the Green New Deal, illustrates a dual commitment to energy security and sustainability. In contrast, Japan's energy policy experienced a dramatic shift after the 2011 Fukushima disaster, moving away from nuclear power toward renewable energy and efficiency. This comparative analysis of South Korea and Japan provides valuable insights into energy policy, and energy structure in resource-constrained, advanced economies in terms of CO2 emissions reduction.

Furthermore, this study highlights how SVAR provides a more accurate framework for understanding energy policies' impacts, demonstrating the importance of accounting for contemporaneous effects between variables. By comparing reduced form VAR with SVAR, the findings emphasize that SVAR enables more realistic evaluations of energy policy impacts, offering policymakers valuable insights into the differential effects of renewables and fossil fuels on emissions. The results offer valuable insights for policymakers, showing how different energy sources like renewables and fossil fuels affect emissions in South Korea and Japan, helping to design more effective and sustainable energy policies.

2 Literature review

Many studies have analysed the causal relationships between various factors, including energy mix, CO_2 emissions, and economic growth, using various dynamic time series methodologies. The reduced form VAR and Granger causality test have been widely used in research. Some findings from these studies show results that differ from generally accepted energy policy effects.

Belaïd and Zrelli (2019)'s empirical study in Mediterranean countries indicates that in short-term the results of reduced for VAR show that renewable energy consumption significantly positively Granger causes CO_2 emissions and on the other hand, non-renewable energy consumption significantly negatively Granger causes CO_2 emissions. Aslan et al. (2022)'s panel VAR approach result shows that neither renewable energy consumption nor fossil fuel energy consumption has a significant causal impact on CO_2 emissions. Moreover, it was found that, although not statistically significant, renewable energy consumption has a positive causal impact on CO_2 emissions, while fossil fuel energy consumption has a negative causal impact on CO_2 emissions. The research results of Dogan and Seker (2016) in the EU indicate that, according to the results of the Granger causality test based on reduced form VAR, non-renewable energy does not have a causal impact on CO_2 emissions. Instead, CO_2 emissions have a unidirectional causal impact on non-renewable energy. Dong et al. (2018) indicates that Granger causality test based on reduced form VAR shows that in the short-run fossil fuel electricity, nuclear electricity, and renewable electricity all Granger cause positively and statistically significantly CO_2 emissions.

Meanwhile, some recent studies have used SVAR models to empirically analyse the causality between the energy sector and other factors. Narayan et al. (2008) applied a SVAR model with zero short-run restrictions to examine the relationship between electricity consumption and GDP in G7 countries. They concluded that, except for the United States, electricity consumption has a positive causation effect on GDP, and except for Italy, GDP has a positive causation effect on electricity consumption. Tiwari (2011) researched the causal relationship between renewable energy, GDP, and CO_2 emissions using the SVAR model in India and concluded that renewable energy positively causes GDP and negatively causes CO_2 emissions, while GDP positively causes CO_2 emissions. Pan et al. (2019) applied a SVAR model using Directed Acyclic Graphs (DAG) in Bangladesh to analyse forecast error variance decomposition (FEVD) and found that financial development and trade openness have a greater impact on technical innovation, and that financial development, trade openness, and technical innovation significantly affect energy intensity. Bruns et al. (2021) applied a SVAR model to the United States and found that energy efficiency has a negative causal relationship with energy consumption in the short term, but it does not have a causality impact in the long term. Calcagnini et al. (2016) applied a SVAR model with long-run restrictions in Italy and concluded that supply shocks have a permanent effect on energy intensity and pollution, whereas demand shocks have a transitory effect on energy intensity and pollution. Işık et al. (2024) analysed the causal relationships between the Domestic-Export/Re-Export ratio, Climate Policy Uncertainty, CO_2 emissions, and the Industrial Production Index in the United States using the SVAR model. They concluded that an increase in the Domestic-Export/Re-Export ratio increases CO_2 emissions, but an increase in Climate Policy Uncertainty does not affect CO_2 emissions. Oryani et al. (2020) applied a SVAR model with long-run restrictions in Iran to examine the causal relationship between GDP, renewable energy, and CO_2 emissions. They found that an increase in renewable energy does not reduce CO_2 emissions but does increase GDP, while an increase in GDP leads to an increase in CO_2 emissions.

Author(s)	Period	Country /region	variables	Restrictions method	results
Narayan et al. (2008)	(USA) 1970-2002 (others) 1960-2002	G7 countries	Electricity Consumption, GDP	Zero short-run restrictions	EC↑ → GDP↑ (except for the USA) GDP↑ → EC↑ (except for Italy)
Tiwari (2011)	1965-2009	India	RE, GDP, CO_2 *ordering: RE→ GDP→CO_2	Long-run restrictions	RE↑ → GDP↑, CO_2↓, GDP↑ → CO_2↑
Pan et al. (2019)	1976-2014	Bangladesh	GDP, Financial Development, Trade Openness, Technical Innovation, Energy Intensity	Directed acyclic graphs (DAG)	Variance Decomposition: FD, TO → TI, FD, TO, TI → EI,
Bruns et al. (2021)	Jan.1992-Oct.2016 1st 1973-3rd 2016	USA	GDP, Electricity Consumption, Energy Price, Energy Efficiency	Independent Component Analysis	EE↑ →(Short-Run) EC↓, (Long-Run) $\overline{EC}$
Calcagnini et al. (2016)	1961–2010 (quarterly data)	Italy	Supply·Demand shocks, Energy Intensity, Pollution	Long-run restrictions	Supply-shocks → (permanent) EI, Pol Demand-shocks → (transitory) EI, Pol
Isık et al. (2024) **Gondwana Research**	Feb.2002-Nov.2021	USA	Domestic-Export/Re-Export ratio, Climate Policy Uncertainty, CO_2, Industrial Production Index	Long-run restrictions	DE/RE↑ → CO_2↑, CPU↑ → CO_2↑(x)
Oryani et al. (2020) **energies**	1980-2016	Iran	GDP, RE, CO_2	Long-run restrictions	RE↑ → CO_2↓(x), GDP↑ GDP↑ → CO_2↑

*** EC (electricity consumption), FD (financial development), TO (trade openness), TI (technical innovation), EI (energy intensity), P_e (energy price), EE (energy efficiency), Pol (pollution)**

Table 2 Research on the energy sector using SVAR

3 Methodology

In this research there are five variables; CO_2, GDP, RE, NE and FE, where CO_2 represents CO_2 emissions per capita, GDP is real GDP per capita, RE is renewable electricity per capita, NE is nuclear electricity per capita, and FE is fossil fuel electricity per capita. The reduced form VAR model considers that all variables are endogenous and a current variable is determined by the lagged all variables.

Assuming the lag is one, the reduced form VAR model is shown as follows:

$$CO_{2\,t} = \alpha_{10} + \alpha_{11}CO_{2\,t-1} + \alpha_{12}GDP_{t-1} + \alpha_{13}\,RE_{t-1} + \alpha_{14}\,NE_{t-1} + \alpha_{15}\,FE_{t-1} + e_{1t} \quad (1)$$

$$GDP_t = \alpha_{20} + \alpha_{21}CO_{2\,t-1} + \alpha_{22}GDP_{t-1} + \alpha_{23}RE_{t-1} + \alpha_{24}\,NE_{t-1} + \alpha_{25}\,FE_{t-1} + e_{2t} \quad (2)$$

$$RE_t = \alpha_{30} + \alpha_{31}CO_{2\,t-1} + \alpha_{32}GDP_{t-1} + \alpha_{33}RE_{t-1} + \alpha_{34}NE_{t-1} + \alpha_{35}\,FE_{t-1} + e_{3t} \quad (3)$$

$$NE_t = \alpha_{40} + \alpha_{41}CO_{2\,t-1} + \alpha_{42}GDP_{t-1} + \alpha_{43}RE_{t-1} + \alpha_{44}NE_{t-1} + \alpha_{45}FE_{t-1} + e_{4t} \quad (4)$$

$$FE_t = \alpha_{50} + \alpha_{51}CO_{2\,t-1} + \alpha_{52}GDP_{t-1} + \alpha_{53}RE_{t-1} + \alpha_{54}NE_{t-1} + \alpha_{55}FE_{t-1} + e_{5t} \quad (5)$$

$* \; E(e_{it}) = 0,\ cov\left(e_{it}, e_{i(t+s)}\right) = 0,\ cov\left(e_{it}, e_{jt}\right) \neq 0$

Reduced form VAR model does not include current variables in explanatory variables, allowing for the application of OLS to estimate the coefficients. The error terms (e_{it}) are not correlated with their own past values, but the error terms in different equations have non-zero covariance with each other, implying that the error terms may include contemporaneous effects of the explanatory variables. From the results of reduced form VAR model, Granger causality test can be easily conducted: If the estimated coefficient of lagged explanatory variable is statistically significant, the explanatory variable Granger causes the dependent variable.

In contrast, the SVAR model incorporates contemporaneous relations into the equations. Therefore, OLS cannot be applied to it due to the problem of endogeneity.

Assuming that the lag is one, the SVAR model is expressed as follows.

$$CO_{2\,t} = \alpha_{10} + \alpha_{11}CO_{2\,t-1} + \alpha_{12}GDP_{t-1} + \alpha_{13}\,RE_{t-1} + \alpha_{14}\,NE_{t-1} + \alpha_{15}\,FE_{t-1} + \alpha_{16}GDP_t + \alpha_{17}\,RE_t + \alpha_{18}\,NE_t + \alpha_{19}\,FE_t + \epsilon_{1t} \quad (6)$$

$$GDP_t = \alpha_{20} + \alpha_{21}CO_{2\,t-1} + \alpha_{22}GDP_{t-1} + \alpha_{23}RE_{t-1} + \alpha_{24}\,NE_{t-1} + \alpha_{25}\,FE_{t-1} + \alpha_{26}CO_{2\,t} + \alpha_{27}RE_t + \alpha_{28}\,NE_t + \alpha_{29}\,FE_t + \epsilon_{2t} \quad (7)$$

$$RE_t = \alpha_{30} + \alpha_{31}CO_{2\,t-1} + \alpha_{32}GDP_{t-1} + \alpha_{33}RE_{t-1} + \alpha_{34}NE_{t-1} + \alpha_{35}FE_{t-1} + \alpha_{36}CO_{2\,t} + \alpha_{37}GDP_t + \alpha_{38}NE_t + \alpha_{39}FE_t + \epsilon_{3t} \quad (8)$$

$$NE_t = \alpha_{40} + \alpha_{45}CO_{2\,t-1} + \alpha_{42}GDP_{t-1} + \alpha_{43}RE_{t-1} + \alpha_{44}NE_{t-1} + \alpha_{45}FE_{t-1} + \alpha_{46}CO_{2\,t} + \alpha_{47}GDP_t + \alpha_{48}RE_t + \alpha_{49}FE_t + \epsilon_{4t} \quad (9)$$

$$FE_t = \alpha_{50} + \alpha_{51}CO_{2\,t-1} + \alpha_{52}GDP_{t-1} + \alpha_{53}RE_{t-1} + \alpha_{54}NE_{t-1} + \alpha_{55}FE_{t-1} + \alpha_{56}CO_{2\,t} + \alpha_{57}GDP_t + \alpha_{58}RE_t + \alpha_{59}NE_t + \epsilon_{5t} \quad (10)$$

* $E(\epsilon_{it}) = 0,\ cov\left(\epsilon_{it}, \epsilon_{i(t+s)}\right) = 0,\ cov\left(\epsilon_{it}, \epsilon_{jt}\right) = 0$

What we can estimate from the empirical data are the reduced form VAR equations so we need to identify more than the observed results to estimate SVAR equations. Therefore, in SVAR, identifying restrictions are necessary and a critical issue. To identify a SVAR with five variables, we need a total of 55 identifications: 50 (=10*5) coefficients of the variables in the equations (6)-(10) and 5 variances of error terms (ϵ_i). However, only 45 identifications are possible from empirical data through the reduced form VAR: 30(=6*5) coefficients of variables in the equations (1)-(5), and 5 variances and 10 covariances[13] of the error terms (e_t). Therefore, we must impose 10 restrictions on identifying to estimate the SVAR model. The identifying restriction cannot be resolved from empirical data but must be based on theory or empirical consideration (Levendis, 2018).

There are mainly three identifying restriction methods in the SVAR model: zero restrictions, such as Cholesky decomposition; long-run restrictions, introduced by Blanchard and Quah in 1988; and sign restrictions. Among the five variables, there are recursive orders, where one variable is affected by other contemporaneous variables and a causal order exists in which some variables respond with lags to shocks in other variables. Therefore, this research employs the zero restrictions method, specially Cholesky decomposition, for identifying restrictions in the model. With five endogenous variables in the model, we establish an order based on which variable affects the others first, i.e., more exogenous variables are listed first in the order than more endogenous variables. If there are five variables, there are 5!, i.e., 5*4*3*2*1=120 ordering cases. Determining the ordering of these five variables

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[13] There are 5 error terms; therefore, there are 10 (=$_5C_2$) covariances among them.

should be theory-based, as the data alone cannot determine this ordering.

Among the five variables, RE, NE and FE should be placed first, followed by GDP and CO_2 emissions last. Energy use is the main cause of GDP and CO_2 emissions. And CO_2 emissions per capita is a by-product of aggregate output, therefore, GDP is placed before CO_2 emissions (Calcagnini et al., 2016). Among RE, NE and FE, RE usually has priority over NE and FE in entering electricity market, and FE normally supplements the gap between total electricity demand and electricity supply from RE and NE. Therefore, among electricity mix, RE is placed fist and then NE, and FE is the last (Charfeddine and Kahia, 2019).

Conclusively, the order is arranged as follows.

Order of variables: RE → NE → FE → GDP → CO_2 emissions

Based on the estimation of SVAR model, orthogonal impulse response functions (IRF) and Forecast Error Variance Decomposition (FEVD) can be estimated. The IRF represents the partial change in a variable at time $t + s$ with respect to a shock (error term) at time t, assuming the error terms at times $t + s + 1$ and beyond are zero. The IRF not only demonstrates the direct and contemporaneous impact between variables but also the indirect impact that pass through two or more variables. This makes the IRF more accurate and effective in analysing causal relationships between factors compared to the Granger

Variable	Abbreviation	Unit	Period	Source
CO_2 emission per capita	CO_2	Ton per capita	1971-2021	OECD
Real GDP per capita	GDP	US dollar (2015 constant)	1971-2021	OECD
Renewable Energy generation per capita	RE	kWh per capita	1971-2021	OECD
Nuclear energy generation per capita	NE	kWh per capita	1971-2021	OECD
Fossil fuel energy generation per capita	FE	kWh per capita	1971-2021	OECD

Table 3 description and source of data

causality test (Levendis (2018). IRF can be estimated from reduced form VAR, though it is not orthogonal. FEVD illustrates how much of the forecast error variance of a variable can be attributed to its own shocks and to the shocks in other variables within the model over time.

4 Data and results

The data used in this research are summarized in Table 2.

To achieve a normal distribution, the variable values are converted to logarithmic form. The analysis focuses on South Korea and Japan, with the analysis period spanning from 1971 to 2021 (51 years).

In the following, we examine reduced form VAR and SVAR and calculate the IRF and FEVD from the reduced form VAR and SVAR, following the processes outlined in Figure 1, using the data. (Levendis, 2018).

First, to avoid the problem of spurious regression, augmented Dickey–Fuller test for unit root is conducted. The results show that in both Korea and Japan, all variables are non-stationary at the level, but become statistically significantly stationary in the first difference for both trend and no-trend cases.[14] Therefore, we conduct the analysis using the first-

1. make sure that the data are stationary

2. determine the number of lags

3. Estimate the VAR

4. Verify that the estimated VAR model is stable

5. Calculate the IRFs from reduced form VAR and
OIRFs and FEVDs from SVAR.

Figure 10 Flow of analysis

difference values of the variables.

Second, to determine the optimal lag in the VAR model, we calculate the values of AIC,

[14] The detailed test results are in Appendix.

Dependent variable	Lagged explanatory variable				
	dln RE_{t-1}	dln NE_{t-1}	dln FE_{t-1}	dln GDP_{t-1}	dln $CO_{2\ t-1}$
dln RE_t	-0.624*** (0.000)	0.104** (0.044)	-0.649* (0.084)	-2.542** (0.014)	1.580* (0.071)
dln NE_t	-0.736** (0.037)	0.288** (0.031)	-0.622 (0.524)	3.413 (0.204)	-0.079 (0.972)
dln FE_t	0.091 (0.283)	-0.016 (0.611)	0.209 (0.371)	0.467 (0.468)	0.039 (0.943)
dln GDP_t	-0.021 (0.461)	0.005 (0.626)	-0.029 (0.716)	0.600*** (0.006)	-0.231 (0.212)
dln $CO_{2\ t}$	0.014 (0.745)	0.020 (0.239)	0.026 (0.837)	0.420 (0.227)	-0.100 (0.733)

Table 4 Results of reduced form VAR for South Korea

HQIC, SBIC, and FPE, which are the criteria in selecting the optimal lag length for the VAR model by balancing the trade-off between the model's fit to the data and its complexity. HQIC and SBIC identified lag 0, while AIC and FPE identified lag 1 as the optimal lag[15]. Since AIC and FPE suggest lag 1 and generally these criteria are more focused on capturing dynamics in the data, we adopt lag 1 as the optimal lag.

Next, the results of estimating the reduced form VAR and SVAR are as follows.

The estimated results of reduced form VAR for South Korea are in Table 3. According to Table 3, the only lagged variable that significantly affects GDP is GDP itself, and no lagged variables significantly affect CO_2 emissions. This result is consistent with the Granger Causality test result.

[15] The detailed test results are in Appendix.

Regarding the estimation of the SVAR, after running STATA statistics package with the variable order of 'RE → NE → FE → GDP → CO_2 emissions', we obtain the estimation of the contemporaneous effects of the explanatory variables on the dependent variables as Table 4. Since the variable ordering is set as 'RE → NE → FE → GDP → CO_2 emissions' in Table 4, the coefficients of all contemporaneous explanatory variables for the dependent variable RE are constrained to 0. Among the contemporaneous explanatory variables for NE, the coefficients of FE, GDP, and CO_2 are constrained to 0. For FE, the coefficients of GDP and CO_2 among the contemporaneous explanatory variables are constrained to 0, and for GDP, the coefficient of CO_2 is constrained to 0. In Table 4, FE shows a significantly positive causal effect on CO_2 emissions, which is consistent with the theory of energy policy effects that fossil fuel generation is the main cause of CO_2 emissions in the energy sector. Additionally, FE exhibits a significantly positive causal effect on GDP. On the other hand, looking at the causal effect of RE on CO_2 emissions, an increase in RE significantly increases CO2 emissions contemporaneously. However, an increase in RE contemporaneously decreases FE significantly, and the decrease in FE reduces CO_2 emissions. Therefore, to understand the net effect of RE on CO_2 emissions, we must consider not only the direct effect but also the indirect effect through the reduction in FE. Conclusively, an increase in

Dependent variable	Contemporaneous explanatory variable				
	dln RE_t	dln NE_t	dln FE_t	dln GDP_t	dln $CO_{2\ t}$
dln RE_t	-	0 (constrained)	0 (constrained)	0 (constrained)	0 (constrained)
dln NE_t	-0.143 (0.700)	-	0 (constrained)	0 (constrained)	0 (constrained)
dln FE_t	-0.328*** (0.000)	-0.042 (0.146)	-	0 (constrained)	0 (constrained)
dln GDP_t	0.029 (0.352)	0.019* (0.063)	0.185*** (0.000)	-	0 (constrained)
dln $CO_{2\ t}$	0.051** (0.047)	0.002 (0.846)	0.308*** (0.000)	0.862*** (0.000)	-

Table 5 The contemporaneous effect of explanatory variables on dependent variable derived from SVAR in South Korea * p-value in parenthesis (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

RE reduces CO_2 emissions, although it is not statistically significant, as demonstrated through the OIRF explained later. It shows that the reduced form VAR cannot detect indirect causality, whereas the OIRFs derived from the SVAR include all indirect effects. This makes the OIRFs more advantageous than the Granger Causality test in detecting causality (Levendis, 2018).

Next are the results of the reduced form VAR analysis and the SVAR analysis for Japan. The results of the reduced form VAR for Japan are shown in Table 5. Lagged FE has a significantly positive effect on CO_2 emissions. Lagged RE also shows a significantly positive effect on CO_2 emissions at the 10% level, suggesting that an increase in lagged RE leads to an increase in CO_2 emissions under 10% significance level, which is contrary to the expected effect of energy policies. There are no lagged factors found to have an effect on

Dependent variable	Lagged explanatory variable				
	dln RE_{t-1}	dln NE_{t-1}	dln FE_{t-1}	dln GDP_{t-1}	dln $CO_{2\ t-1}$
dln RE_t	-0.535*** (0.001)	-0.005 (0.910)	-0.509 (0.299)	-0.465 (0.517)	0.620 (0.353)
dln NE_t	-1.298** (0.023)	0.383** (0.013)	-2.047 (0.232)	2.241 (0.372)	-0.791 (0.735)
dln FE_t	0.269*** (0.005)	0.009 (0.718)	0.471 (0.103)	-0.153 (0.718)	-0.124 (0.754)
dln GDP_t	0.0292 (0.451)	0.00543 (0.601)	0.111 (0.338)	0.304* (0.073)	-0.117 (0.459)
dln $CO_{2\ t}$	0.105* (0.077)	0.006 (0.710)	0.463*** (0.009)	-0.011 (0.966)	-0.305 (0.206)

Table 6 the result of reduced form VAR for Japan

*p-value in parenthesis (*** p<0.01, ** p<0.05, * p<0.1))

GDP.

After running STATA with the variable order of 'RE → NE → FE → GDP → CO_2 emissions', the estimation of the contemporaneous effects of explanatory variables on the dependent variable is obtained, as shown in Table 6. Not only FE and but also NE have significantly positive contemporaneous causal effects on CO_2 emissions. However, both NE and RE exhibit a significantly negative contemporaneous causal effect on FE, resulting in a net negative impact on CO_2 emissions by reducing FE.

Fourthly, a test is conducted to determine whether the estimated VAR model is stable. If the VAR model is unstable, the forecast is unreliable and the relationships between variables may have changed over time (Levendis, 2018). As seen in Figure 2, in both South Korea and Japan, all the eigenvalues lie inside the unit circle. This indicates that the VAR

Dependent variable	Contemporaneous explanatory variable dln RE_t	dln NE_t	dln FE_t	dln GDP_t	dln $CO_{2\ t}$
dln RE_t	-	0 (constrained)	0 (constrained)	0 (constrained)	0 (constrained)
dln NE_t	0.134 (0.795)	-	0 (constrained)	0 (constrained)	0 (constrained)
dln FE_t	-0.300*** (0.000)	-0.073*** (0.000)	-	0 (constrained)	0 (constrained)
dln GDP_t	0.058 (0.101)	0.031*** (0.001)	0.291*** (0.000)	-	0 (constrained)
dln $CO_{2\ t}$	-0.002 (0.952)	0.024** (0.026)	0.493*** (0.000)	0.059* (0.000)	-

Table 7 The contemporaneous effect of explanatory variables on dependent variable derived from SVAR in Japan * p-value in parenthesis (*** p<0.01, ** p<0.05, * p<0.1))

models meet the stability condition and are correctly specified.

Lastly, IRFs from the reduced-form VAR, along with OIRFs and FEVDs from the SVAR, are calculated for South Korea and Japan. The results for South Korea are shown in Figures 3 and 4, while those for Japan are presented in Figures 5 and 6.

In South Korea, IRFs from the reduced-form VAR indicate that the energy mix does not significantly affect CO2 emissions over time. However, OIRFs from the SVAR reveal that

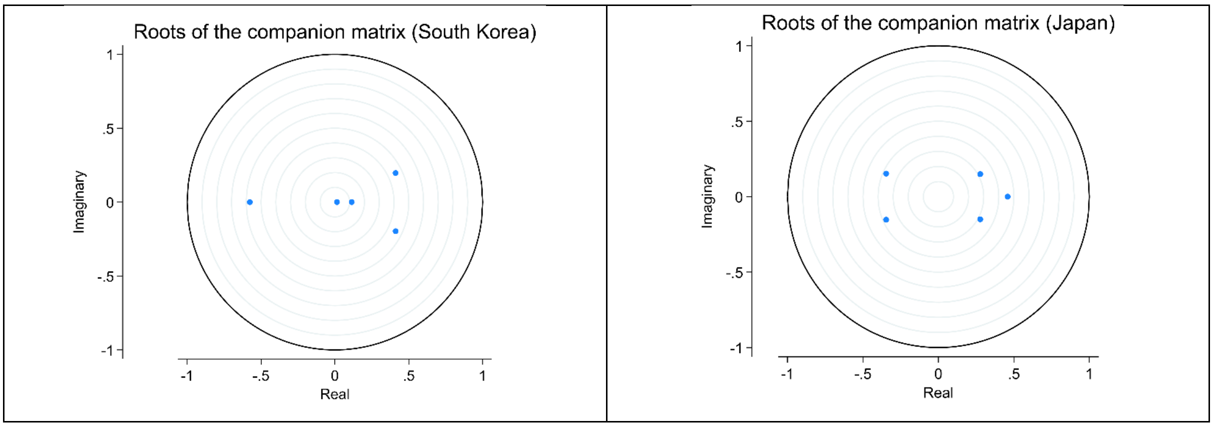

Figure 11 stability test of the VAR models

fossil fuel electricity (FE) significantly increases CO2 emissions contemporaneously, and renewable electricity (RE) significantly decreases CO2 emissions contemporaneously at the 10% confidence level. For Japan, IRFs from the reduced-form VAR show that FE significantly increases CO2 emissions at time 1, while RE increases CO2 emissions over time, though this effect is not statistically significant. In contrast, OIRFs from the SVAR indicate that FE significantly increases CO2 emissions contemporaneously, whereas RE significantly decreases CO2 emissions contemporaneously at the 10% confidence level.

Figure 7 shows the FEVDs derived from South Korea's SVAR model. As expected, the variation of CO_2 emissions is primarily due to the shocks in FE, with approximately 50% of CO_2 emissions variation attributed to shocks in FE after 1 year continuously. The shock of GDP contributes to the variation of CO_2 emissions by around 20%, while those of RE and NE each contribute less than 5%. In Figure 8, FEVDs from SVAR in Japan show that the variation in CO_2 emissions is due to shocks in FE by around 50%, then due to its own shocks by around 30%, and next to shocks in RE by around 20%.

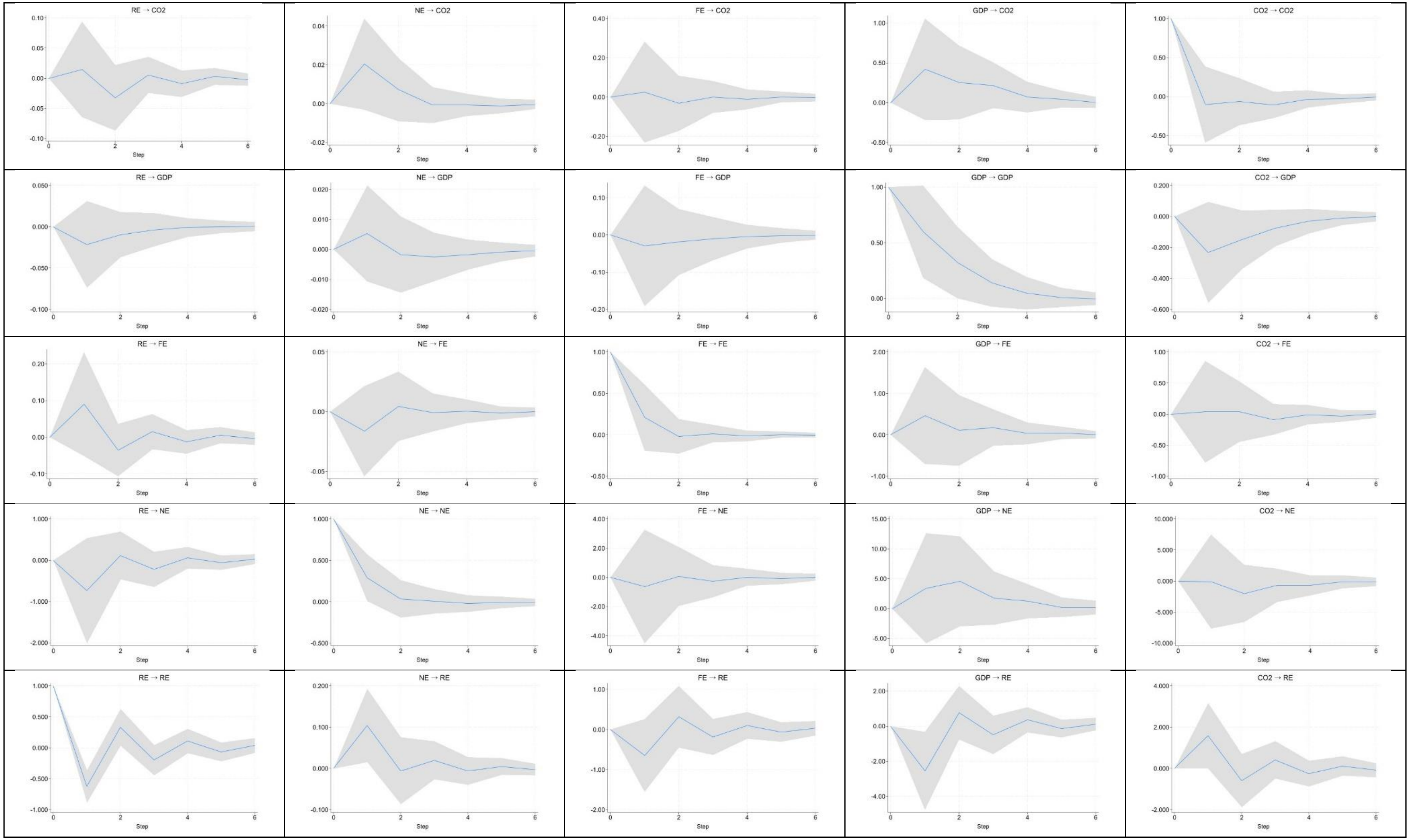

Figure 12 irf from var (South Korea) (Gray area: 95% confidence interval) * C.I is calculated from bootstraping method.

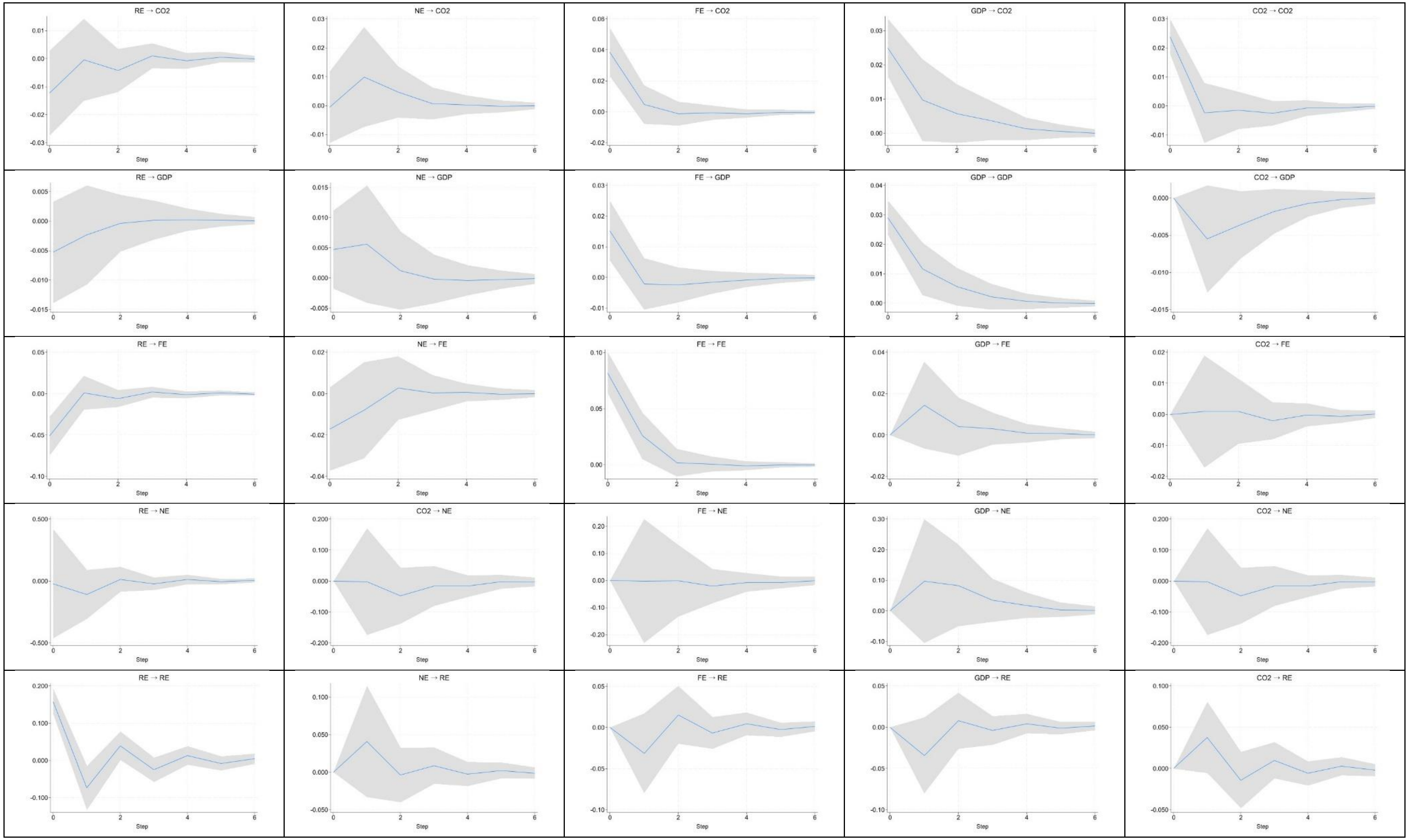

Figure 13 oirf from svar (South Korea) (Gray area: 95% confidence interval * C.I is calculated from bootstrapping method

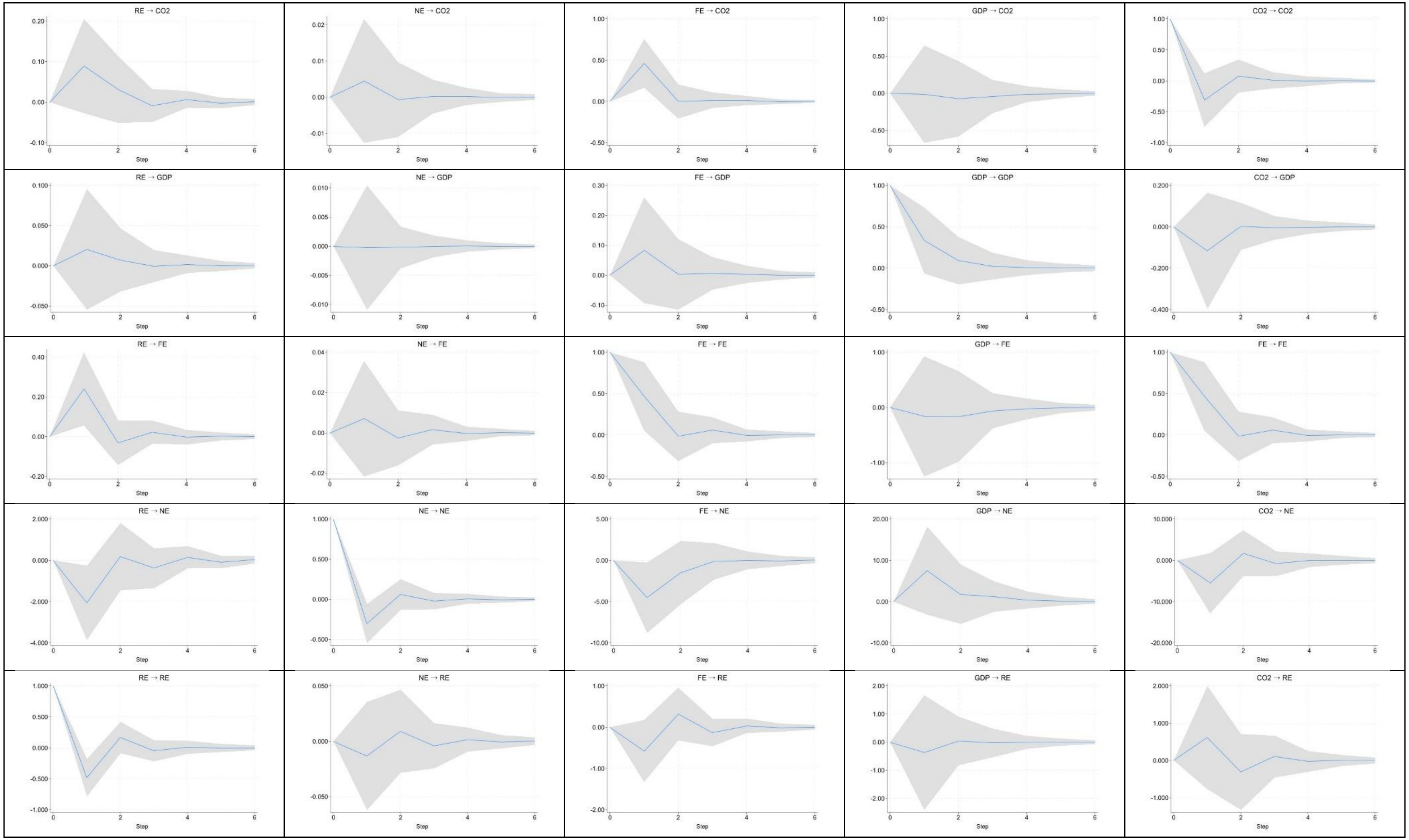

Figure 14 irf from var (Japan) (Gray area: 95% confidence interval) * C.I is calculated from bootstrapping method

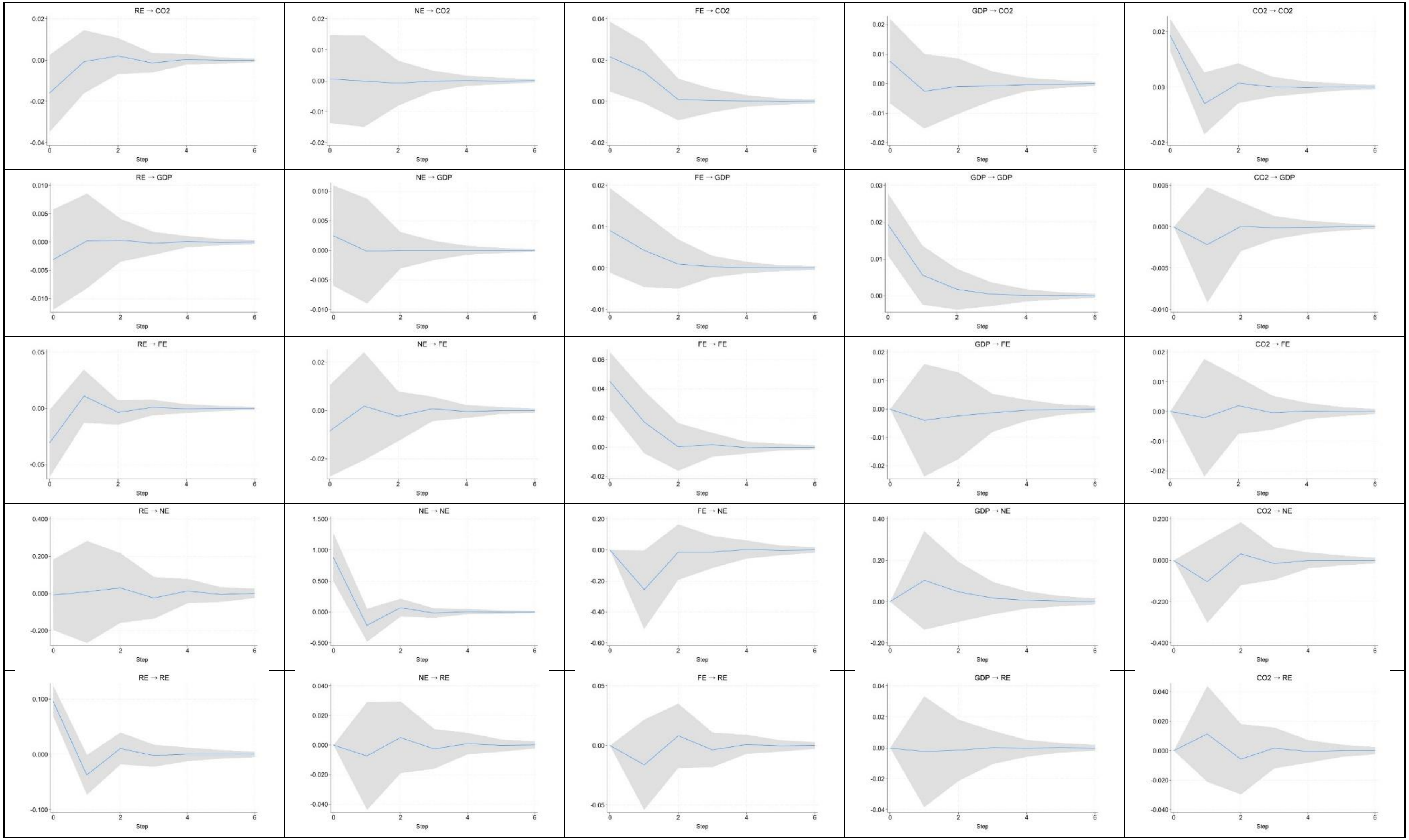

Figure 15 oirf from svar (Japan) (Gray area: 95% confidence interval) * C.I is calculated from bootstrapping method

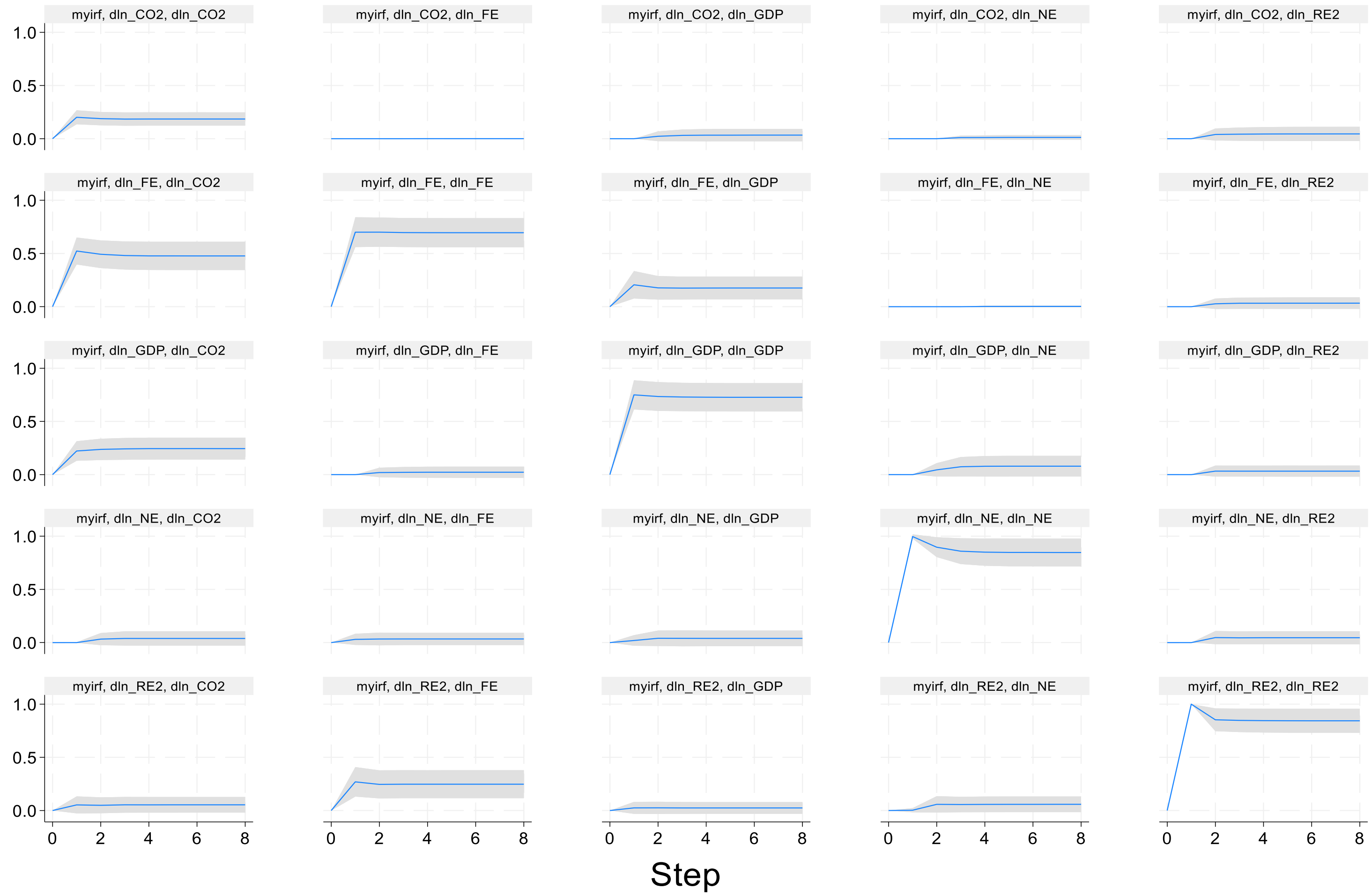

Figure 16 FEVD (South Korea)

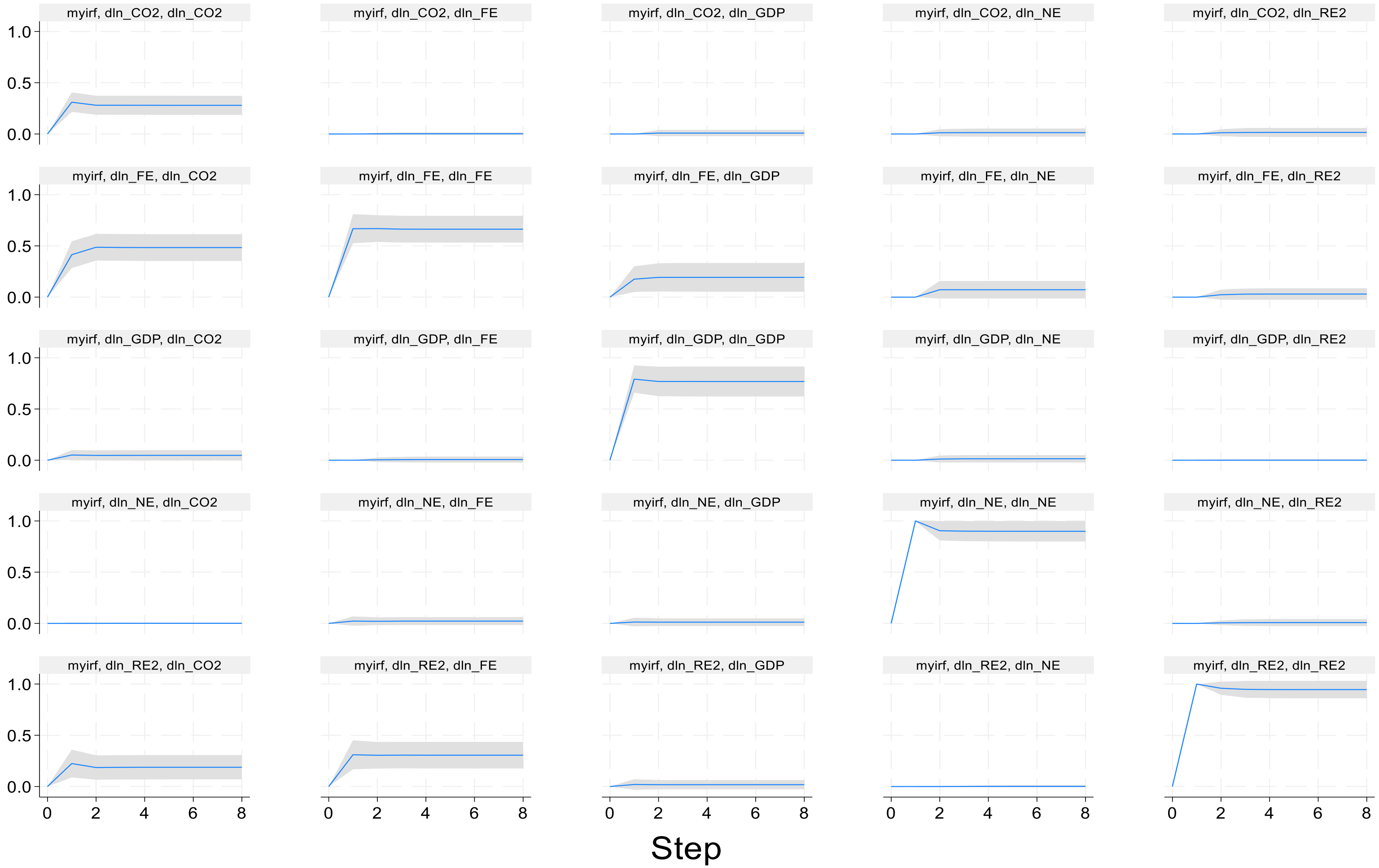

Figure 17 FEVD (Japan)

Comparing the IRFs from reduced-form VAR and OIRFs from SVAR, focusing on the causal impact on CO_2 emissions, is summarized in Table 9. In South Korea, the reduced form VAR model indicates that changes in the energy mix do not have a significant impact on CO_2 emissions. However, the SVAR model shows that FE has a significant positive causal relationship with CO_2 emissions contemporaneously.

In the case of Japan, the IRFs from reduced form VAR model indicates that FE positively and significantly affect CO_2 emissions, but RE also positively affect CO_2 emissions though not significantly, raising questions about the effectiveness of energy policies. However, the OIRF results from the SVAR model show that FE has a significant positive causal impact and RE a significant negative causal impact on CO_2 emissions at 10% C.I.

The analysis results of the two models show very different results regarding energy policy impact. This is because the reduced VAR model does not consider the contemporaneous effects of the energy mix on CO2 emissions, leading to distorted results.[16]

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[16] Appendix 1 and 2 show the simple contemporaneous correlation between $\ln GDP$ and $\ln CO_2$ and other variables without controlling for other variables. These Figures suggest that the contemporaneous impact between $\ln GDP$ and $\ln CO_2$ and other variables is high. Therefore, it implies analysing causal relationships between variables without considering the contemporaneous impact is likely to lead to significant errors.

< South Korea >

causality	Reduced form VAR (IRF)	SVAR (OIRF)
RE → CO_2	Positive but not statistically significant causality	Negative but not statistically significant causality
NE → CO_2	Positive but not statistically significant causality	Positive but not statistically significant causality
FE → CO_2	Positive but not statistically significant causality	Positive and statistically significant causality
GDP → CO_2	Positive but not statistically significant causality	Positive and statistically significant causality

< Japan >

causality	Reduced form VAR (IRF)	SVAR (OIRF)
RE → CO_2	Positive but not significant causality	Negative and statistically significant causality
NE → CO_2	Positive but not statistically significant causality	Negative but not statistically significant causality
FE → CO_2	Positive and statistically significant causality	Positive and statistically significant causality
GDP → CO_2	Negative but not statistically significant causality	Positive but not statistically significant causality

Table 8 comparing the results of reduced form VAR and SVAR

5 Conclusion and policy implications

Economic growth, the environment, and energy mix are crucial policy areas that closely influence each other. The VAR model considers all variables in the system as endogenous. This approach enables the analysis of causal relationships in both bilateral and multilateral time series data.

To identify the causal relationships between GDP, CO_2 emissions, and the mix of renewable energy, non-renewable energy, and fossil energy, many studies have employed traditional VAR, i.e., reduced form VAR, and conducted Granger causality tests based on the results. However, the reduced form VAR, which do not consider contemporaneous impacts between variables, can lead to incorrect conclusions when analysing the causal relationships between them. This is because the energy mix tends to have a contemporaneous effect rather than a lagged effect on CO_2 emissions and GDP, especially when the term period unit is long, such as a year. If the results of reduced form VAR yield incorrect conclusions, policymakers in energy policy and scholars analysing the effectiveness of energy policies might make erroneous policy decisions or misinterpret the effects of policies based on flawed analysis. For example, the IRF and Granger causality test result from reduced form VAR might show that FE does not have a significant causal effect on increasing CO_2 emissions, while RE does have a significant causal effect on increasing CO_2 emissions (Belaïd and Zrelli, 2019; Aslan et al., 2022; Dogan and Seker, 2016; Dong et al., 2018). Such analysis results could fundamentally undermine the effectiveness of energy policy and significantly diminish trust in energy policy. In this study, we empirically demonstrated, using the cases of South Korea and Japan, how reduced form VAR tests can lead to incorrect conclusions in analysing the causal relationships between economic growth, CO_2 emissions, and energy mix. On the other hand, we showed that SVAR can more accurately derive policy effects and causal relationships.

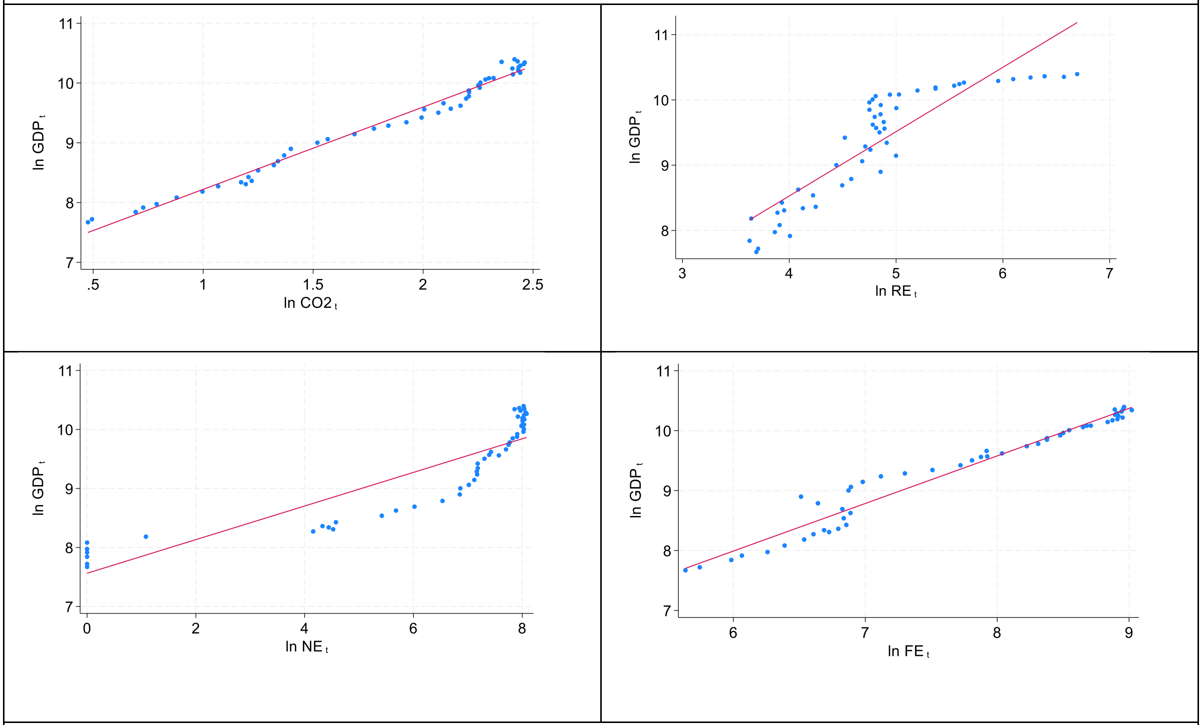
These analysis results imply that caution is needed when applying the reduced form VAR model results in analysing the causal relationships between GDP, CO_2 emissions, and the energy mix. Furthermore, applying the SVAR model can provides a more accurate method for deriving causal relationships. However, while the SVAR model offers the advantage of more accurately analysing reality, it also has the limitation that applying this model requires somewhat complex procedures and assumptions, such as identifying restrictions. Identifying restrictions must be based on theory rather than observed data, and if the identifying restrictions are incorrectly set, such as incorrect variable ordering, it can lead to erroneous analysis results. Therefore, identifying restrictions must be grounded on a solid and robust theoretical foundation.

Appendix

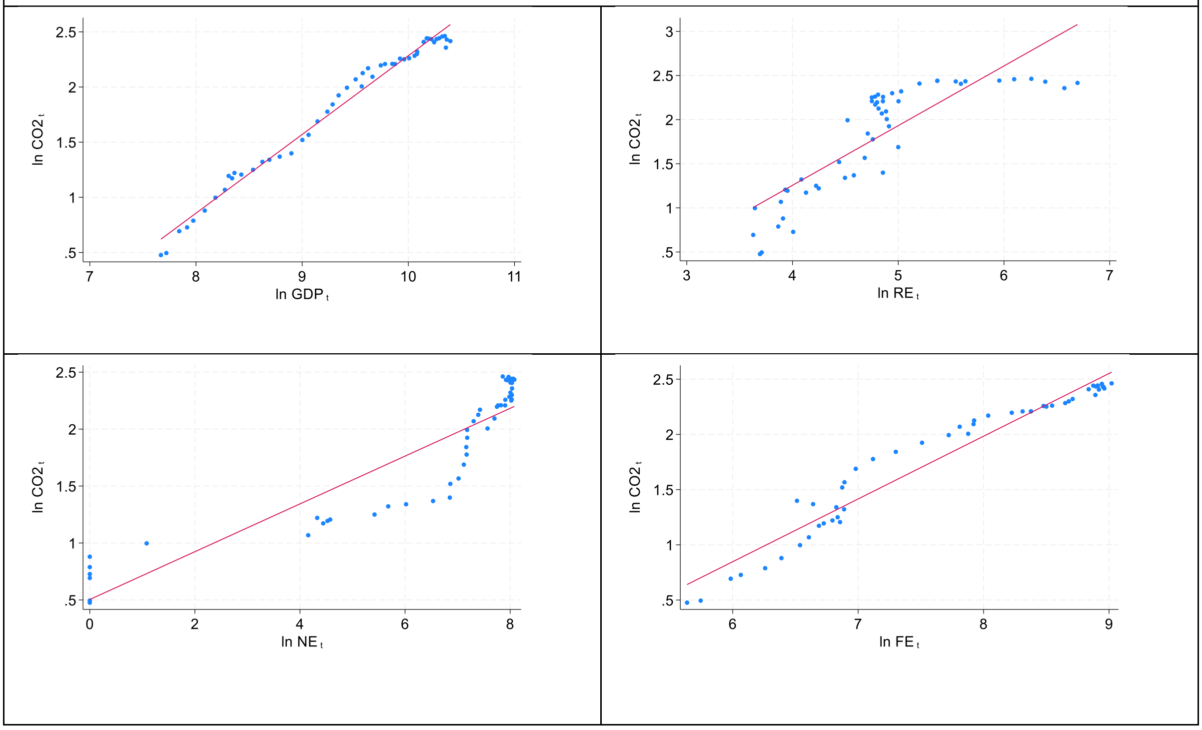
1 Contemporaneous correlation between variables

1.1 South Korea

Contemporaneous correlation between ln GDP and other variables

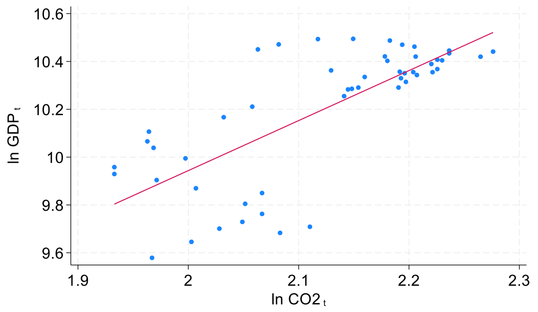


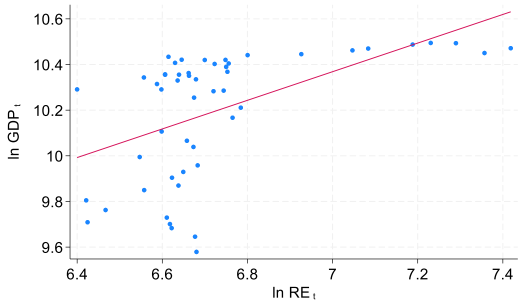
Contemporaneous correlation between ln CO_2 and other variables

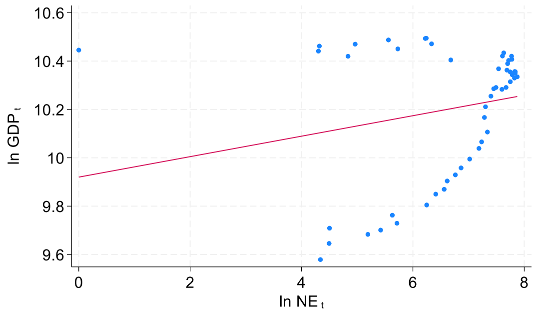


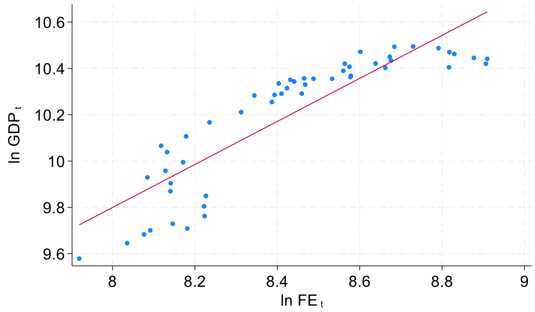
1.2 Japan

Contemporaneous correlation between ln GDP and other variables

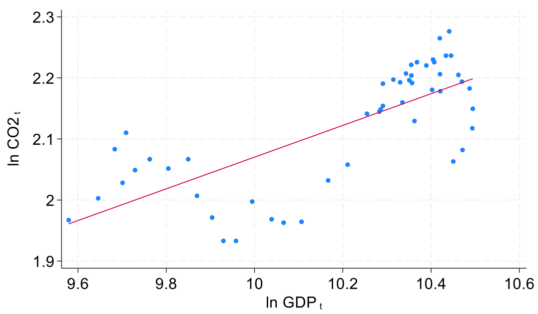


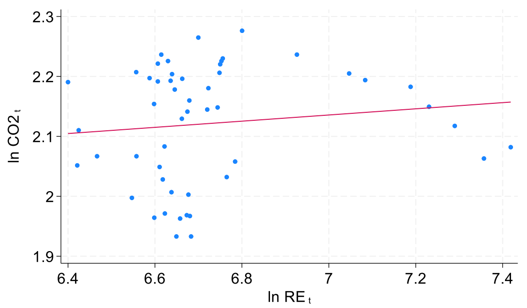


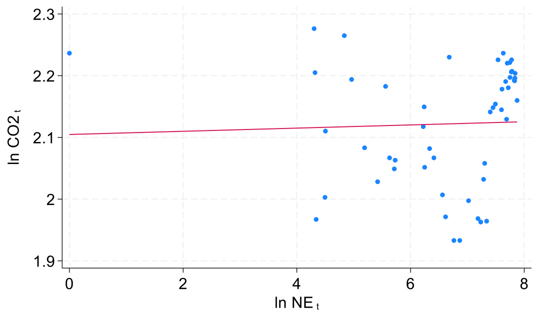


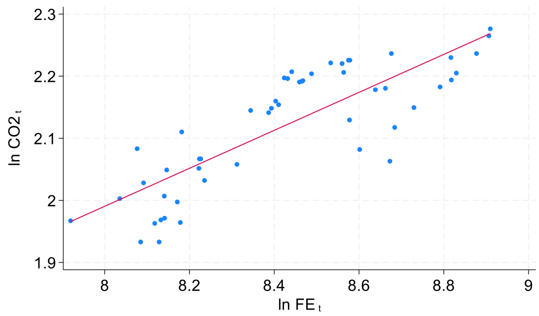


Contemporaneous correlation between ln CO_2 and other variables









2 the results of augmented Dickey–Fuller test for unit root (using 1 lag)

2.1 South Korea

	Level				first difference			
	Without trend		With trend		Without trend		With trend	
	statistic	P-value	statistic	p-value	statistic	P-value	statistic	p-value
ln RE	1.314	0.997	-0.343	0.989	-5.961	0.000	-6.192	0.000
ln NE	-2.737	0.068	-1.925	0.642	-4.544	0.000	-5.369	0.000
ln FE	-1.818	0.371	-1.719	0.742	-4.582	0.000	-4.748	0.001
ln GDP	-3.947	0.002	-0.153	0.992	-3.545	0.007	-5.323	0.000
ln CO2	-3.811	0.003	-1.075	0.933	-4.283	0.001	-5.402	0.000

2.2 Japan

	level				first difference			
	Without trend		With trend		Without trend		With trend	
	statistic	P-value	statistic	p-value	statistic	P-value	statistic	p-value
ln RE	1.124	0.995	-0.578	0.980	-5.943	0.000	-6.317	0.000
ln NE	-2.086	0.250	-1.820	0.695	-3.054	0.030	-3.329	0.062
ln FE	-1.466	0.550	-2.089	0.552	-5.485	0.000	-5.459	0.000
ln GDP	-2.803	0.057	-0.785	0.967	-4.252	0.007	-5.206	0.000
ln CO2	-1.833	0.364	-1.725	0.740	-5.558	0.000	-5.459	0.000

According to the results of ADF test, they are nonstationary at level but all stationary at first difference.

3 determine the optimal number of lags

3.1 results of lag-order selection criteria for South Korea

Lag	FPE	AIC	HQIC	SBIC
0	5.3e-11	-9.47946	-9.405*	-9.2807*
1	4.0e-11*	-9.75676*	-9.31001	-8.56417
2	6.0e-11	-9.40168	-8.58263	-7.21526
3	8.9e-11	-9.10374	-7.9124	-5.92349
4	1.3e-10	-8.94455	-7.38092	-4.77048

3.2 results of lag-order selection criteria for Japan

According to lag-order selection criteria, optimal lag for both countries is 1.

Lag	FPE	AIC	HQIC	SBIC
0	6.20E-13	-13.9173	-13.841*	-13.7062*
1	5.7e-13*	-14.0118*	-13.5538	-12.7451
2	1.00E-12	-13.5002	-12.6606	-11.178
3	2.30E-12	-12.8538	-11.6325	-9.47605
4	2.90E-12	-12.9694	-11.3665	-8.53609

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(Chapter 3) The Impact of Energy Mix and Economic Growth on CO_2 Emissions: A Comparison of Countries with and without Nuclear Power Plants

1 Introduction

In the last few decades, climate change has been identified as the major environmental problem facing the world (IPCC 2018; McKinsey Global Institute 2020). In recent years, there has been increased global attention to the need for reducing carbon dioxide (CO_2) emissions from energy production and other industrial activities. Energy is a crucial requirement for economic production, thereby contributing to economic expansion and societal progress (Adhikari and Chen 2012; Apergis and Danuletiu 2012; Gbadebo and Okonkwo 2009). However, it also stands as a significant contributor to the emission of greenhouse gases (Belaïd and Zrelli 2019). The energy sector is the most important source of CO_2 emissions. Energy is used in three sectors: electricity, heating, and transportation. The electrification of economies is gradually expanding through the widespread adoption and utilization of electricity as a primary source of energy for various applications and industries in both the clean energy transition and user convenience (Marques et al. 2016; IEA). In this regard, this paper's focus is on the electricity sector among energy consumption areas, with the aim of analyzing its impact on CO_2 emissions. There are three main energy sources in electricity generation: fossil fuel generation, renewable energy generation and nuclear energy generation. Renewable and nuclear energies, unlike fossil fuel energy, are considered to emit negligible amounts of CO_2 and play an important role in mitigating climate change. Fossil fuel generation, renewable energy generation and nuclear energy generation have different effects on CO_2 emissions and have the potential to even impose further effects in the future. Therefore, not only changing total electricity consumption but also changing the electricity mix among fossil fuel generation, renewable energy generation and nuclear energy generation critically influences CO_2 emissions in a country. On the other hand, the correlation between economic growth and environmental pollution has been investigated within the framework of the Environmental Kuznets Curve (EKC). The original proposition of the EKC hypothesizes an inverted U-shaped relationship between environmental pollution, such as CO_2 emissions, and GDP per capita. Grossman and Krueger (1991), in a study analyzing the possible environmental impacts of the North American Free Trade Agreement (NAFTA) in the early 1990s, argued that there may be a relationship between per capita income and per capita environmental pollution such that it initially increases and subsequently decreases after it reaches a specific threshold in a reverse-U-shaped pattern. According to this hypothesis, the degradation of the environment escalates with respect to GDP per capita during the early stages of economic growth but diminishes after it reaches a certain threshold. The veracity of this hypothesis remains uncertain, depending on the estimation technique, data timeframe and type, and country attributes. Numerous studies have been conducted to assess the efficacy of the EKC while controlling for variables such as energy consumption, population, trade openness, urbanization, renewable energy or fossil fuel energy. Thus far, various studies have been undertaken to analyze the influence of GDP and energy factors on CO_2 emissions.

Nuclear and renewable power are considered non-CO2-emitting electricity sources. Nuclear power has several advantages, including high energy density, reliability, and long-term economic benefits, but it faces challenges such as radioactive waste, security threats, and high initial costs. Currently, around 30 countries operate nuclear power plants, with only 11 of the 38 OECD countries doing so. Whether nuclear power is part of a country's energy mix can significantly impact CO_2 emissions in various ways.

The relationship between the presence of nuclear power systems and the validity of the EKC hypothesis remains unexplored. While studies exist on how oil production affects the relationship between energy mix, economic growth, and CO2 emissions (Aslan et al., 2022), none have analyzed nuclear power's influence. Nuclear systems are distinct due to their high entry barriers, acceptance issues due to intense opposition from local residents and strong path dependence, as their establishment creates vested interests, making both adoption and phase-out challenging (Fouquet, 2016). Analyzing how nuclear power impacts the EKC hypothesis offers valuable insights into this dynamic, shedding light on its role in shaping sustainable energy policies.

This study tests the validity of the Environmental Kuznets Curve (EKC) hypothesis in two groups of OECD countries: those with nuclear power plants and those without, using annual data from 1971 to 2021. It also examines the effects of changes in the energy mix on CO_2 emissions within the EKC framework. By comparing nuclear, renewable, and fossil fuel generation, the study determines which energy source is most effective in reducing CO2 emissions. This analysis is important not only from a scientific perspective but also from a policy viewpoint, as it helps assess the effects of energy mix changes on emissions.

The analysis is conducted using a dynamic panel Auto-Regressive Distributed Lag (ARDL) model, with results checked for robustness using sub-sample group. The findings show that the EKC hypothesis holds in countries with nuclear power plants but not in those without. In both groups, increased electricity consumption leads to higher CO2 emissions. Substituting fossil fuel electricity (FE) with renewable electricity (RE) or nuclear electricity (NE) reduces CO2 emissions in nuclear-powered countries. While RE is generally more effective than FE in reducing emissions in nuclear-powered countries, in countries with a high reliance on nuclear power, substitution with NE proves to be more effective than with RE.

In non-nuclear countries, replacing FE with RE also significantly reduces CO_2 emissions, and the reduction rate of RE is higher than that of RE in nuclear-powered countries. Trade openness had no significant effect on CO_2 emissions, while population growth had a notable reduction impact.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature; Section 3 describes the data and methodology; Section 4 presents the empirical analysis and primary results; and Section 5 concludes with a summary and policy implications.

2 Literature Review

Many scholars have investigated the relationship between economic growth and environmental degradation using time-series data from individual countries or groups of several countries. The analyses have been expanded to account for various factors, including energy consumption, urbanization, financial development, renewable energy, fossil fuel energy, nuclear energy, trade openness, public expenditures, tourism revenue, oil consumption, gas consumption, and other factors.

Mensah et al. (2019) examined the causal links among carbon emissions, economic growth, fossil fuel energy consumption and oil prices by using a panel of 22 African countries during the 1990–2015 period. They used the PMG panel ARDL estimation method to explore the causalities among variables in the long term and short term.

Using data from 151 countries spanning the years 1971 to 2013, Kibria et al. (2019) analyzed the correlation between the proportion of fossil fuels in the energy mix and per capita income. They discovered a polynomial connection between the fossil fuel percentage and income, which they referred to as the "Energy Mix Kuznets Curve" (EMKC).

Koc and Bulus (2020) conducted research on the relationships between per capita GDP, per capita energy consumption, per capita renewable energy consumption, trade openness, and per capita CO_2 emissions in Korea from 1971 to 2017. Their findings indicate an N-shaped relationship between per capita CO_2 emissions and per capita GDP, which does not support the EKC hypothesis in Korea. They concluded that when per capita energy consumption increases, per capita CO_2 emissions increase; however, when per capita renewable energy consumption or trade openness increases, per capita CO2 emissions decrease. Zhang (2018) examined the correlation between CO_2 emissions, trade openness, and the import and export of goods in Korea. His analysis revealed a positive correlation between CO_2 emissions and trade openness, exports, and imports. Additionally, the author concluded that an EKC exists in Korea. The impact of nuclear and renewable energy sources on environmental quality in Korea was studied by Pata and Kartal (2023). They argue that nuclear energy has a positive effect on environmental quality, while renewable energy does not have a significant long-term impact on the environment. Sufyanullah et al. (2022) conducted an analysis of the connection between urbanization and CO_2 emissions in Pakistan for the 1975–2018 period. Their findings indicated that an increase in urbanization resulted in a subsequent increase in CO_2 emissions. Eldowma et al. (2023) examined the case of Sudan from 1971 to 2019 and found strong correlations among population, CO_2 emissions, and GDP. While population growth contributed to economic expansion, it also led to increased electricity consumption and, subsequently, higher CO_2 emissions. Marques et al. (2016) investigated the relationship between the electricity mix and economic growth in France on monthly and annual bases. They indicated that nuclear energy generation had a positive impact on economic growth and a reduction in CO_2 emissions, whereas renewable energy generation had a negative impact on economic growth.

Shaari et al. (2020) analyzed the impact of the consumption of oil and gas among energy usage on CO_2 emissions in 20 Organization of Islamic Cooperation (OIC) countries. They concluded that while GDP growth led to a long-term increase in CO_2 emissions, it had no short-term effect. On the other hand, population growth temporarily reduced CO_2 emissions but had no long-term impact. Furthermore, they found that the consumption of oil and gas led to an increase in CO_2 emissions in both the short and long run, with oil consumption having a greater effect on increasing CO_2 emissions than gas consumption.

Sreenu (2022) analyzed the impact of key macroeconomic variables—FDI, crude oil price, and GDP—on CO_2 emissions in India using data spanning 1990 to 2020. His research results support the EKC hypothesis in India. He also indicated that shocks in crude oil prices have a significant influence on CO_2 emissions, while FDI inflows support the 'pollution haven' hypothesis. Dauda et al. (2021) concluded that there is an inverted U-shaped relationship between innovation and CO_2 emissions and that renewable energy use lessens CO_2 emissions across nine African countries during the period from 1990 to 2016.

Belaïd and Zrelli (2019) researched the causal relationships between renewable energy electricity, non-renewable energy electricity, GDP, and CO_2 emissions for 9 Mediterranean countries during the 1980-2014 period. The analysis results showed that non-renewable energy electricity consumption and GDP contribute to an increase in CO_2 emissions, while renewable energy generation consumption reduces CO_2 emissions. The key findings of these researches are summarized in Table 1.

Author(s)	Period	Country /region	Other factors considered	Methodology	Results
Marques et al. (2016)	(2010-2014) monthly	France	GDP, REE, NE	ARDL	$NE\uparrow\rightarrow GDP\uparrow, CO_2\downarrow$ $REE\uparrow\rightarrow GDP\uparrow, CO_2\downarrow$,
Pata and Kartal (2023)	(1977-2018)	Korea	GDP, NE, RE	ARDL	LCC, EKC valid $NE\uparrow\rightarrow CO_2\downarrow$, $RE\uparrow\nrightarrow CO_2\downarrow$,
Zhang (2018)	(1971-2013)	Korea	GDP, non-FF, TO	ARDL	EKC valid, $\text{Non-FF}\uparrow\rightarrow CO_2\downarrow$, $TO\uparrow\rightarrow CO_2\downarrow$,

Mensah et al. (2019)	(1990-2015)	22 African countries	GDP, FF, oil price	PMG ARDL	FF ↔ GDP, CO_2 Oil price → GDP, fossil fuel, CO_2
Koc and Bulus (2020)	(1971-2017)	Korea	GDP, RE, TO, EC	ARDL bounds test	EKC invalid, GDP, EC↑→CO_2↑, RE, TO↑→CO_2↓
Shaari et al. (2020)	(1990-2017)	20 OIC countries	GDP, population oil consumption, gas consumption	Panel ARDL	(LR) GDP, oil, gas↑→CO_2↑, population↑→CO_2↓ (SR) GDP, population↑↛ CO_2↑ Oil, gas↑→CO_2↑
Dauda et al. (2021)	(1990-2016)	9 African countries	GDP, innovation, TO	GMM, OLS	Inverted U-shape between innovation and CO_2 RE↑→CO_2↓ EKC valid
Sreenu (2022)	(1990-2020)	India	GDP, crude oil use, FDI inflows	ARDL, Non-linear ARDL	EKC valid, Crude oil price↑→CO_2↓ Crude oil use↑→CO_2↑ FDI inflows↑→CO_2↑
Belaïd and Zrelli (2019)	(1980-2014)	9 Mediterra-nean countries	GDP, REE, non-REE	PMG ARDL	(LR) non-REE↔CO_2 GDP→ CO_2, non-REE REE→ CO_2 (SR) GDP↔REE↔ CO_2 Non-REE↔GDP↔REE
Sufyanullah et al. (2022)	(1975-2018)	Pakistan	GDP, EC, urbanization	ARDL VECM	GDP, urbanization↑→ CO_2↑
Eldowman et al. (2023)	(1971–2019)	Sudan	GDP, population, electricity consumption	ARDL	population↑→GDP↑→electricity consumption↑→ CO_2↑

*Note: TO(trade openness), RE(renewable energy), REE(renewable energy electricity) NE(nuclear energy), FF(fossil fuel energy), EC(energy consumption), FF(fixed-effect model), RE(random-effect model), LCC(load capacity curve), OIC(Organization of Islamic Cooperation), LR(long run), SR(short run)

Table 1 Empirical literature on the relation between CO2 emissions and other factors

3 Data and methodology

3.1 Data and model

This study investigates two groups of OECD member countries: one group of 12 countries with nuclear power plants and another group of 10 countries without nuclear power plants[1]. The analysis covers a period of 51 years, from 1971 to 2021.

Countries with nuclear generation (12)		Countries without nuclear power plants (10)	
1	Belgium	1	Australia
2	Finland	2	Austria

[1] Among the 38 OECD members, countries that previously operated nuclear power plants but no longer do, as well as countries with insufficient data, are excluded from this research.

3	France	3	Chile
4	Germany	4	Colombia
5	Japan	5	Costa Rica
6	Korea	6	Denmark
7	Mexico	7	Greece
8	Netherlands	8	Luxembourg
9	Spain	9	Norway
10	Sweden	10	Portugal
11	UK		
12	USA		

Table 2 analysis target of two groups of countries

The analysis model is primarily based on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, an extended version of the IPAT model. The IPAT model suggests that environmental impact (I) is determined by three factors: population (P), affluence (A), and technology (T), as represented by the following equation.

$$I = P \times A \times T \tag{1}$$

The STIRPAT model, introduced by Dietz and Rosa (1994) as an extended version of the IPAT model, is expressed as follows. Additional regressors can be included in the equation depending on the research objectives.

$$I = \alpha P^{\beta 1} A^{\beta 2} T^{\beta 3} \tag{2}$$

When eq (2) is transformed into logarithmic form, it results in eq (3).

$$\ln I = \ln \alpha + \beta_1 \ln P + \beta_2 \ln A + \beta_3 \ln T \tag{3}$$

Based on the STIRPAT model, the following equation is derived.

$$lnCO_{2\ i,t} = \alpha_0 + \alpha_1\ lnGDP_{i,t} + \alpha_2(lnGDP_{i,t})^2 + \alpha_3 \ln EC_{i,t} + \alpha_4 \ln RE_{i,t} + \alpha_5 \ln NE_{i,t}$$
$$+ \alpha_6\ ln\, TO_{i,t} + \alpha_7\ ln\, POP_{i,t} + \beta_i + \epsilon_{i,t} \qquad (4)$$

In the eq (4), CO_2 denotes carbon emissions per capita, EC denotes electricity consumption per capita[2], RE denotes renewable energy generation per capita, NE denotes nuclear energy generation per capita, TO denotes trade openness and POP denotes population. i denotes the country, and t denotes the year. The details of the dataset are summarized in Table 2. All the series used in the empirical analysis are in natural logarithm form.[3] β_i represents the specific effect of a certain country i on CO_2.

Variable	Abbreviation	Unit	Period	Source
CO_2 emission per capita	CO_2	Ton per capita	1971-2021	OECD
Real GDP per capita	GDP	US dollar (2015 constant)	1971-2021	OECD
Electricity consumption per capita	EC	kWh per capita	1971-2021	OECD
Renewable Energy generation per capita	RE	kWh per capita	1971-2021	OECD
Nuclear energy generation per capita	NE	kWh per capita	1971-2021	OECD
Trade openness =(export+import)/GDP*100	TO	%	1971-2021	OECD

[2] Electricity is produced from fossil fuel, nuclear energy, or renewable energy sources. Therefore, total electricity consumption is the sum of fossil fuel generation (FE), nuclear energy generation (NE), and renewable energy generation (RE). In other words, EC = FE + NE + RE.

[3] When transforming logarithms, values of 0 are lost and become missing data. To avoid this problem, one is added to each value of RE and NE. It means that in eq (1), '$\ln RE$' and '$\ln NE$' actually refer to $\ln(RE+1)$ and $\ln(NE+1)$, respectively.

Population	POP	Number	1971-2021	OECD

Table 3 Description and sources of data

In eq (4), fossil fuel generation is omitted. The electricity mix consists of three energy sources: fossil fuel, nuclear energy, and renewable energy. Electricity consumption, i.e., the sum of fossil fuel generation, nuclear energy generation and renewable energy generation, is incorporated as an explanatory variable in eq (4). Therefore, adding fossil fuel generation as an explanatory variable to eq (4) may generate serious multicollinearity and cause unclear analysis results when interpreting eq (4).

Since EC is included and 'fossil fuel generation' is not included in the explanatory variables in eq (4), we can interpret the results such that α_4 represents the percent change in CO_2 emissions when renewable energy generation is increased by 1% as a replacement for fossil fuel generation, while α_5 represents the percent change in CO_2 emissions when nuclear energy generation is increased by 1% as a replacement for fossil fuel generation. In essence, α_4 and α_5 signify the effects on CO_2 emissions when fossil fuel generation is replaced by renewable energy generation and nuclear energy generation, respectively. Coefficients α_1 and α_2 are related to the EKC hypothesis. If $\alpha_1 > 0$ and $\alpha_2 = 0$, a positive linear relationship exists between CO_2 emissions and economic growth, implying that the EKC hypothesis does not hold. Conversely, if $\alpha_1 > 0$ and $\alpha_2 < 0$, the EKC hypothesis holds.

The coefficients α_4 and α_5 represent the effects of changes in the electricity mix, as explained previously.

	Group of Countries with nuclear power plants					Group of countries without nuclear power plants				
Variables	Obs.	Mean	S.D	Max	Min	Obs.	Mean	S.D	Min	Max
$\boldsymbol{ln\, CO_2}$	612	2.056	0.500	0.476	3.097	510	1.654	0.974	-0.371	3.906
$\boldsymbol{ln\, GDP}$	612	10.151	0.589	7.670	11.033	510	9.925	0.977	7.822	11.630
$(\boldsymbol{ln\, GDP})^2$	612	103.386	11.459	58.828	121.717	510	99.460	19.131	61.180	135.256
$\boldsymbol{ln\, EC}$	612	8.794	0.717	5.770	9.806	510	8.230	0.991	6.040	10.364
$\boldsymbol{ln\, RE}$	612	6.592	1.716	0.000	9.290	510	7.111	1.532	1.672	10.362
$\boldsymbol{ln\, NE}$	612	6.747	2.100	0.000	9.095	510	0.000	0.000	0.000	0.000
$\boldsymbol{ln\, TO}$	612	8.363	0.645	6.757	9.775	510	8.538	0.694	7.161	10.561
$\boldsymbol{ln\, POP}$	612	17.467	1.144	15.344	19.620	510	15.756	1.147	12.744	17.757

Table 4 Descriptive statistics

Table 4 presents descriptive statistics of the explanatory variables and the dependent variable.

3.2 Dynamic ARDL panel model

With respect to the time series panel data, there are two models: the static panel model and the dynamic panel model. The static panel model estimators are OLS estimators, and the fixed effect model and the random effect model, are representative examples of the static panel model. The static panel model assumes a static relationship between variables. However, if there is a unit root in the time series data, the OLS estimator may not be a consistent estimator, and a spurious regression problem may occur with the OLS estimator.

Due to these issues, the dynamic panel model is employed in this context. The dynamic panel model addresses these issues of serial correlation and unit root by including lagged dependent and explanatory variables as explanatory variables. Among the various dynamic panel models available, this research employs the panel autoregressive distributed lag (ARDL) model. This model evaluates the cointegration and long-term equilibrium relationships among variables and captures dynamic effects in both the long and short term.

Pesaran et al. (1995) introduced the mean group (MG) estimator for panel data, which allows for variation in intercepts, slopes of the explanatory variables, and error variance across different groups of countries. Another study by Pesaran et al. (1999) developed the pooled mean group (PMG) estimator, which combines both average and pooled characteristics for panel data analysis. The PMG method allows for different intercepts, coefficients of explanatory variables, and error variations in the short run across country groups, while the coefficients of the explanatory variables remain similar in the long run across different country groups.

The generalized $ARDL(p, q, q, \dots, q)$ model for t=1, 2, ..., T periods and i=1, 2, ..., N country groups is as follows.

$$lnCO_{2\,i,t} = \sum_{k=1}^{p} \lambda_{ik}\, lnCO_{2\,i,t-k} + \sum_{k=0}^{q} \delta_{ik}\, X_{i,t-k} + \omega_i + \varepsilon_{it} \quad (5)$$

The panel $ARDL(p, q, q, \dots, q)$ model mentioned above can be explained as follows. X_{it} represents the $(k \times 1)$ vector of explanatory variables for country group i. The fixed effect of group i is denoted by ω_i. The coefficients of the lagged dependent variable $lnCO_{2\,i,t}$, i.e., λ_{ik}, indicate the scalars in the equation. Finally, the coefficient vector (1× k) is indicated by δ_{ik}.

In general, the representation of eq (5) in the form of a vector error correction model (VECM) at equilibrium can be reparametrized as follows (Mensah et al. 2019):

$$\Delta \ln CO_{2\,i,t} = \sum_{k=1}^{p-1} \lambda_{ik}\, \Delta \ln CO_{2\,i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta X_{i,t-k} + \varphi_i \left(ln\, CO_{2\,i,t-1} + \beta_i'\, X_{i,t-1} \right) + \omega_i + \varepsilon_{it} \qquad (6)$$

In eq (6), $\lambda_{ik}, \delta_{ik}'$ represent short-run coefficients. $(lnCO_{2\,i,t-1} + \beta_i'\, X_{i,t-1})$ is the error correction term (ECT), and φ_i represents the group-specific error correction coefficient, i.e., the speed of adjustment, which is expected to be negative. β_i' indicates the long-run coefficient.

The following equation relies on eq (6) and encompasses all the variables that are considered in the model of eq (4).

$$\begin{aligned}\Delta \ln CO_{2\,i,t} = {} & \beta_0 + \sum_{k=1}^{p-1} \lambda_{ik}\, \Delta \ln CO_{2\,i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta \ln GDP_{i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta \left(\ln GDP_{i,t-k} \right)^2 + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta \ln EC_{i,t-k} \\ & + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta \ln RE_{i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta \ln NE_{i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta\, ln\, TO_{i,t-k} + \sum_{k=0}^{q-1} \delta_{ik}'\, \Delta\, ln\, POP_{i,t-k} \\ & + \varphi_i \left[\ln CO_{2\,i,t-1} + \beta_i' \left(\ln GDP_{i,t-1}, (\ln GDP_{i,t-1})^2, \ln EC_{i,t-1}, \ln RE_{i,t-1}, \ln NE_{i,t-1}, ln\, TO_{i,t-1}, ln\, POP_{i,t-1} \right) \right] \\ & + \omega_i + \varepsilon_{it} \qquad (7)\end{aligned}$$

4 Results

Countries around the world are economically interconnected, which may lead to cross-sectional dependence. In such cases, estimators can be biased and inconsistent, leading to invalid inferences. Therefore, the first step is to conduct a cross-sectional dependence test.

	Group of Countries with nuclear power plants		Group of Countries without nuclear power plants	
Variables	CD test	p-value	CD test	p-value
$\boldsymbol{ln\ CO_2}$	13.083	0.000	12.368	0.000
$\boldsymbol{ln\ GDP}$	56.525	0.000	44.538	0.000
$(\boldsymbol{ln\ GDP})^2$	56.527	0.000	44.481	0.000
$\boldsymbol{ln\ EC}$	50.042	0.000	33.058	0.000
$\boldsymbol{ln\ RE}$	41.191	0.000	35.563	0.000
$\boldsymbol{ln\ NE}$	41.897	0.000	-	0.000
$\boldsymbol{ln\ TO}$	57.076	0.000	45.409	0.000
$\boldsymbol{ln\ POP}$	52.902	0.000	43.531	0.000

Table 5 the results of Pesaran (2015)'s CD test

According to the Table 5, all variables in both groups of countries exhibit cross-sectional dependence.

Next, panel unit root test is conducted. The first-generation unit root test such as LLC, IPS test assume cross-sectional independence, which can lead to misleading results when cross-sectional dependence is present. Therefore, second-generation unit root test, such as Pesaran (2007)'s CIPS test, which is designed to handle cross-sectional dependence, is applied here to check for unit root in the data.

	group of countries with nuclear power plants				group of countries without nuclear power plants			
	At level		At first difference		At level		At first difference	
	constant	Constant +trend	constant	Constant +trend	constant	Constant +trend	constant	Constant +trend
ln CO_2	-2.385**	-2.853**	-6.144***	-6.340***	-2.171	-2.451	-5.886***	-6.256***
ln GDP	-2.376**	-2.602	-5.117***	-5.364***	-1.933	-1.944	-4.562***	-4.843***
(ln GDP)^2	-2.390**	-2.632	-5.163***	-5.358***	-1.923	-1.926	-4.554***	-4.816***
ln EC	-1.983	-2.561	-6.016***	-6.279***	-2.082	-2.214	-5.737***	-6.372***
ln RE	-2.668***	-2.905**	-6.125***	-6.358***	-2.532**	-2.616	-5.734***	-5.971***
ln NE	-2.823***	-3.191***	-5.212***	-5.185***	-	-	-	-
ln TO	-2.227*	-2.280	-5.687***	-5.825***	-2.698***	-2.772*	-5.425***	-5.893***
ln POP	-1.682	-1.991	-2.823***	-3.019***	-0.869	-2.031	-2.077	-2.786*

Table 6 Results of the panel unit root test (CIPS)

Table 6 presents the results of the CIPS unit root test. For the ARDL model to be applicable, all variables must be stationary either at level (I(0)) or at first difference (I(1)). Except for ln POP in the constant case for the non-nuclear power group, all variables are found to be either I(0) or I(1) [4]. This indicate that all variables are stationary at level or first differences. Next, table 7 displays the results of the Pedroni, Kao and Westerlund cointegration tests[5]. The analyses of the cointegration test reveal the presence of cointegration between the dependent variable and the explanatory variables in both country groups.

	group of countries with nuclear power plants	**group of countries without nuclear power plants**
	Statistic	Statistic
Pedroni cointegration test		
Modified Phillips-Perron t	2.0503 **	-0.0443
Phillips-Perron t	-0.8276	-2.8720***

[4] When applying first generation unit root test (ips) for ln POP, the results are I(1) in constant and constant+trend case.

[5] When cross-sectional dependence exists in panel data, the Westerlund panel cointegration test (2007) is generally a more appropriate test for cointegration. However, due to the large number of variables in this model, it is not feasible to apply the Westerlund test. Therefore, traditional cointegration tests were conducted instead.

Kao cointegration test		
Dickey–Fuller t	-1.4576*	0.0297
Unadjusted modified DF t	-1.3737*	-1.8540**
Unadjusted Dickey–Fuller t	-1.5140*	-1.4886*
Westerlund cointegration test		
Variance ratio	-1.5832**	-2.0033**

Table 7 Results of panel cointegration test

The unit root and cointegration test results conducted earlier now indicate the feasibility of applying a panel ARDL VECM using the same dataset.

Table 8 presents the findings from the panel ARDL VECM model, estimated using the STAT statistical package. This model captures both the long-run and short-run effects of the explanatory variables. This study examines how the presence or absence of nuclear power plants affects the relationships between CO2 emissions and various factors, such as GDP, electricity consumption, nuclear energy generation, renewable energy generation, trade openness, and population. Two distinct panel ARDL models are employed: the pooled mean group (PMG) and the mean group (MG) estimations. To determine the more appropriate estimation method between PMG and MG, a Hausman test is conducted. The following analysis focuses on the long-run relationships in light of the long-term equilibrium.

For the group of countries with nuclear power plants, the Hausman chi-square test indicates that the difference in coefficients between the PMG and MG models is systematic, suggesting that the MG estimation is more appropriate than the PMG estimation.

According to the MG analysis findings, the EKC hypothesis holds over the long term in the dynamic panel model in the group countries with nuclear power plants, with electricity consumption, the electricity mix, trade openness and population held constant. The long-run coefficient of $(\ln GDP)^2$ is negative and statistically significant at the 5% level, whereas the coefficient of $\ln GDP$ is positive and statistically significant at the 10% level.

The results of this analysis indicate that, with electricity consumption and the energy mix, etc held constant, as long-term per capita GDP increases, long-term per capita CO2 emissions increase until they reach approximately $22,204; beyond $22,204, per capita CO2 emissions decrease. According to the MG model of the group of countries with nuclear power plants, electricity consumption has a statistically significant and positive effect on CO_2 emissions in the long run and short run. Nuclear energy generation has a significant effect on reducing CO_2 emissions in the long run. This implies that when nuclear energy generation increases by 1% to replace fossil fuel generation, there is a long-run reduction of 0.105% in CO_2 emissions. Renewable energy generation also significantly reduces CO_2 emissions in the long run. Table 8 shows that a 1% increase in renewable energy generation as a substitute for fossil fuel generation results in a substantial and lasting reduction of CO_2 emissions by 0.303%, which is almost three times of nuclear generation case.

	Group of countries with nuclear power plants				Group of countries without nuclear power plants (1)				Group of countries without nuclear power plants (2)			
	PMG		MG		PMG		MG		PMG		MG	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Long-run												
ln GDP	-0.059	0.964	14.632*	0.052	-3.381*	0.067	17.975	0.303	0.110	0.414	0.088	0.782
$(\ln GDP)^2$	-0.003	0.957	-0.731**	0.045	0.204**	0.045	-0.952	0.312	-	-		
ln EC	0.923***	0.000	0.952***	0.000	0.742***	0.000	0.757	0.108	0.587***	0.000	1.074***	0.001
ln RE	-0.082***	0.002	-0.303*	0.084	0.003	0.983	-0.185	0.448	-0.146**	0.022	-0.462***	0.001
ln NE	-0.019***	0.003	-0.105***	0.002	-	-	-	-	-	-		
ln TO	0.003	0.954	0.134	0.571	0.361***	0.006	0.178	0.309	0.631***	0.003	-0.042	0.829
ln POP	-1.047***	0.000	-1.670*	0.070	-1.310***	0.000	-1.735	0.041	-0.641**	0.023	-1.738**	0.047
Short-run												
ECT(− 1)	-0.129***	0.000	-0.388***	0.000	-0.062	0.136	-0.410***	0.000	-0.049	0.139	-0.370***	0.000
Δln GDP	-2.331	0.458	-11.076***	0.001	5.172*	0.050	2.339	0.315	0.784***	0.000	0.588***	0.000
$\Delta(\ln GDP)^2$	0.158	0.331	0.580***	0.001	-0.221	0.107	-0.098	0.441	-	-		
Δln EC	0.433***	0.001	0.308***	0.004	0.474***	0.000	0.394***	0.005	0.528***	0.000	0.300***	0.000
Δln RE	-0.050	0.242	-0.017	0.727	-0.287***	0.000	-0.279**	0.031	-0.316***	0.000	-0.194***	0.000
Δln NE	-0.019*	0.056	-0.001	0.909	-	-	-	-	-	-		
Δln TO	0.059	0.383	-0.071	0.224	0.086	0.101	0.061	0.391	0.041	0.478	0.046	0.503
Δln POP	1.301	0.147	2.150***	0.006	0.378	0.618	2.900**	0.014	1.006	0.176	2.359***	0.006
Constant	1.818***	0.000	-16.843	0.184	1.674	0.157	-1.855	0.863	0.004	0.908	7.077	0.106
	Hausman chi² = 45.02, **p-value**=0.0000				**Hausman chi²** = 77.76 **p-value**= 0.0000				**Hausman chi²** = -9.14 **p-value**=n.a.			
	No. of obs. = 612				No. of obs. = 510				No. of obs. = 510			

Table 8 Results of ARDL ECM (lag = 1)

Next is the analysis results of the group of countries without nuclear power plants in the column 'Group of countries without nuclear power plants (1)' in table 8. Hausman test result supports MG estimation. The EKC does not hold as the coefficients of both ln GDP and $(\ln GDP)^2$ are not statistically significant.

Hence, the ARDL model omitting (ln GDP)2 is conducted to the group of countries without nuclear power plants and the results are shown in the column 'Group of countries without nuclear power plants (2)' in Table 8. The results of the Hausman test do not clearly indicate whether PMG or MG estimation is more appropriate. Therefore, the analysis focuses on the MG estimation. Based on the MG estimation in the column 'Group of countries without nuclear power plants (2),' GDP growth leads to an increase in CO2 emissions, but this effect is not statistically significant. Electricity consumption significantly increases CO2 emissions, while renewable energy generation significantly reduces CO2 emissions. Notably, the reduction effect of RE is greater than that observed in the group of countries with nuclear power plants.

These results imply that countries operating nuclear power plants are more likely to observe the EKC hypothesis due to unique dynamics associated with nuclear energy. Nuclear power, as a low-carbon energy source, significantly reduces CO_2 emissions, allowing countries to decouple economic growth from rising emissions (Sharma et al., 2024;

IEA 2019; Lee et al., 2017). Additionally, nuclear-powered nations often invest in advanced infrastructure and adopt stringent environmental and safety regulations, enabling better emissions management as income levels increase. This aligns with the EKC hypothesis, where emissions decline after reaching a certain level of economic development.

In contrast, countries without nuclear power tend to rely more heavily on fossil fuels, which leads to increasing emissions with economic growth (IEA, 2023; NBER, 2017). These nations may lack robust environmental policies and the infrastructure needed for efficient emissions reductions, making it difficult to achieve the inverted-U pattern of the EKC. For countries choosing to expand renewable energy instead of nuclear power, challenges such as the intermittency of renewable sources like wind and solar, high transition costs from fossil fuel-based infrastructure, and insufficient regulatory frameworks may also hinder the emergence of the EKC. Renewable energy often requires supplementary fossil fuel generation for stability, potentially sustaining emissions during economic growth phases. However, with sustained investments in renewable energy and strong environmental policies, these nations may still achieve an EKC-like pattern over the long term.

In both groups of countries, trade openness does not have a significant effect on CO2 emissions, while population has a statistically significant negative impact on CO2 emissions in the long run. Population growth may reduce per capita CO_2 emissions due to several factors (Swedish Research Council; Casey and Calor, 2016). Urbanization economies of scale improve infrastructure efficiency, enabling centralized energy use and better public transport. Technological advancements driven by higher demand foster renewable energy and efficiency investments. Economic shifts toward less carbon-intensive service sectors lower emissions. Additionally, policy changes and growing environmental awareness in larger populations promote sustainable practices and stricter regulations. These combined factors help explain the observed decline in per capita emissions with population increases.

To verify the robustness of the ARDL model's results, the same model is applied to sub-sample groups as shown in Table 9. Group 1 uses the 1977–2021 data as a sample for 8 out of 12 nuclear-operating countries, excluding 4 countries (i.e., Germany, Netherlands, Mexico, and Japan) where the share of nuclear power generation is less than 5%, and also excluding years when nuclear power generation was not in operation in these 8 countries. Group 2 uses the 1977–2021 data as a sample for 10 non-nuclear countries.

Focusing on long-run relationships, in Group 1, the EKC hypothesis still holds, and $\ln EC$, $\ln RE$, and $\ln NE$ exhibit similar effects on CO_2 emissions as observed in the previous 12 country group of nuclear-operating countries, except that the effect of $\ln NE$ is greater than that of $\ln RE$.

	Group 1				Group 2 (1)				Group 2 (2)			
	PMG		MG		PMG		MG		PMG		MG	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Long-run												
ln GDP	5.976***	0.000	6.962	0.276	-3.373**	0.015	4.844	0.639	0.580***	0.000	0.007	0.983
$(\ln GDP)^2$	-0.282***	0.001	-0.342	0.264	0.192**	0.014	-0.276	0.600				
ln EC	0.662***	0.000	1.219***	0.000	0.908***	0.000	0.643*	0.075	0.733***	0.000	1.278*	0.054
ln RE	-0.043***	0.003	-0.631	0.068	-0.046	0.628	-0.255	0.209	-1.113***	0.000	-0.443**	0.013
ln NE	-0.324***	0.000	-0.284**	0.010								
ln TO	0.137	0.322	0.163	0.195	0.389***	0.000	-0.005	0.976	0.041	0.583	-0.339	0.512
ln POP	-3.084***	0.000	-2.185***	0.000	-1.142***	0.000	-1.370	0.124	-0.791***	0.000	-3.490	0.129
Short-run												
ECT(− 1)	-0.195**	0.029	-0.499***	0.000	-0.091	0.124	-0.448***	0.000	-0.120*	0.083	-0.406***	0.000
Δln GDP	-14.916***	0.000	-16.221***	0.000	6.147***	0.001	3.309	0.131	0.689***	0.000	0.509***	0.001
$\Delta(\ln GDP)^2$	0.742***	0.000	0.808***	0.000	-0.271***	0.003	-0.149	0.208				
Δln EC	0.630***	0.002	0.260**	0.046	0.466***	0.000	0.378***	0.009	0.474***	0.000	0.357***	0.000
Δln RE	-0.109	0.296	0.074	0.445	-0.295***	0.000	-0.252**	0.040	-0.233***	0.001	-0.231***	0.005
Δln NE	-0.123**	0.038	-0.048*	0.072								
Δln TO	0.061	0.301	-0.001	0.993	0.109*	0.073	0.105	0.112	0.116**	0.010	0.093*	0.080
Δln POP	1.190	0.317	3.863**	0.024	0.771	0.358	4.553***	0.008	0.766	0.167	3.126**	0.011
Constant	3.835**	0.023	-0.871	0.954	2.242	0.140	7.902	0.648	1.294*	0.096	7.513*	0.088
	Hausman chi² = 4.20, **p-value**=0.757				**Hausman chi²** = 53.10 **p-value**= 0.0000				**Hausman chi²** = 262.52 **p-value**= 0.0000			
	No. of obs. = 360				No. of obs. = 450				No. of obs. = 450			

Table 9 Results of ARDL ECM for sub-sample groups (1 lag)

In Group 2, the Hausman test results support MG over PMG. The MG results for Group 2 indicate that the EKC hypothesis does not hold, which is consistent with the results of the previous 10 country group of non-nuclear countries.

5 Conclusion and Policy implications

In this paper, I examined the validity of the EKC hypothesis and the impact of the energy mix on CO2 emissions in two groups in OECD members: countries with nuclear power plants and those without.

Based on ARDL ECM results, the group with nuclear power plants supports the validity of the EKC hypothesis, while no evidence of EKC validity was found in the group without nuclear power plants.

In the group with nuclear power plants, the reduction rate of CO2 emissions from renewable energy generation is greater than that from nuclear energy generation. When comparing the impact of renewable energy generation on CO2 emissions reduction between the two groups, the group without nuclear power plants shows a greater reduction effect. Trade openness does not significantly affect CO2 emissions in either group, but population significantly reduces CO2 emissions.

The analysis yields the following policy implications: First, in countries with nuclear power plants, economic growth can contribute to reducing CO_2 emissions once it surpasses a certain turning point, as indicated by the EKC. However, in countries without nuclear power plants, economic growth does not necessarily lead to reduced CO_2 emissions, suggesting that these countries will require additional policy measures to curb emissions as their economies grow. Substituting fossil fuel generation with renewable energy generation has a greater effect on reducing CO_2 emissions than substituting with nuclear energy generation. Additionally, the substitution of fossil fuel generation with renewable energy generation has a greater impact on CO_2 emission reduction in countries without nuclear power plants compared to those with nuclear power plants.

In conclusion, countries without nuclear power plants may have an advantage in reducing CO_2 emissions through the substitution of fossil fuel with renewable energy. However, they are at a disadvantage because economic growth does not have a positive impact on reducing emissions, unlike in countries with nuclear power plants.

This research has the following limitations: First, there is cross-sectional dependence in the panel data, and the CS-ARDL method would provide a more accurate estimation. However, due to the large number of variables in this model and the inability to account for cross-sectional dependence, the CS-ARDL method was not used in this study. Among nuclear-operating countries, some are formulating and implementing medium- to long-term phase-out plans for nuclear and fossil fuel power generation. Analyzing how these plans influence the EKC pattern remains a task for future research.

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