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Impact of Carbon Pricing on Renewable Energy: A Comparative Study of Developing and Developed Countries

Fei Zhao[a]
Chor Foon Tang[b]
Universiti Sains Malaysia

Abstract: The global energy transition is crucial in tackling climate change and achieving sustainable development, with renewable energy playing a central role in replacing fossil fuels. Therefore, many countries have implemented carbon pricing policies to internalise environmental externalities. While most of the existing literature focuses on the impact of such policies on carbon dioxide (CO_2) emissions, their influence on renewable energy capacity remains underexplored. We examine the impact of carbon pricing policies – emissions trading schemes (ETS) and carbon taxes – on renewable energy capacity across 18 developing and 21 developed countries from 2006 to 2022. Given that the standard difference-in-differences (DiD) approach may violate the parallel trends assumption due to cross-country heterogeneity, we employ a combination of propensity score matching (PSM) and staggered DiD to mitigate selection bias and improve causal inference. We find that carbon pricing policies significantly increase renewable energy capacity in developing countries, both in the short run and long run. However, implementation of these policies appears to reduce renewable energy capacity in developed countries, possibly due to policy design, market maturity, or regulatory overlap. The findings highlight the importance of strengthening carbon pricing in developing countries, while developed economies may require more targeted reforms or complementary policies to enhance renewable energy development.

Keywords: Carbon pricing policies, renewable energy capacity, propensity score matching, difference-in-differences method
JEL classification: C32, Q28, Q56

1. Introduction

Renewable energy is one of the most effective solutions to the conflict between climate change and heavy reliance on fossil fuel energy in current economies. Over the last few decades, renewable energy has experienced rapid development. Driven by various environmental policies and international agreements among more than 130 countries, the total renewable energy capacity has increased by 50% in 2023 (International Energy Agency [IEA], 2024). Notably, China holds the largest installed capacity of renewable energy, surpassing 1.45 billion kilowatts in 2023, followed by the United States, Brazil,

[a] Centre for Policy Research, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia. Email: zhaofei@student.usm.my
[b] Centre for Policy Research, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia. Email: tcfoon@usm.my (Corresponding author)

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India and Germany (International Renewable Energy Agency [IRENA], 2023). This rapid growth positions renewable energy as a crucial channel to achieve global goals set by the 28th Conference of the Parties (COP28) to the United Nations Framework Convention on Climate Change (UNFCCC). Many countries have set quantitative environmental targets to meet the COP28 declaration. For instance, the European Union (EU) aims to reduce net greenhouse gas (GHG) emissions by at least 55% by 2030 and become a climate-neutral continent by 2050, raising its 2030 renewable energy targets to a minimum of 42.5%. Additionally, the EU has implemented the Carbon Border Adjustment Mechanism (CBAM) to reduce CO_2 emissions by assigning a fair price to the carbon emitted (European Commission, 2024). Under the 14th Five-Year Plan for a modern energy system, China is determined to achieve a 33% share of all renewable carbon and over 50% of incremental energy consumption from renewable energy (National Energy Administration, 2022).

Despite these commitments to sustainable development, the delayed recognition of the polluter-pays principle has resulted in environmental market failure, where polluters emit GHG without bearing the cost of pollution. Hence, carbon pricing policies become vital for addressing these negative externalities by imposing charges on emissions. Understanding the effectiveness of carbon pricing policies in improving renewable energy generation is crucial. The effectiveness of these policies has been discussed both theoretically and empirically. Theoretical studies suggest that carbon pricing policies can promote economic and structural transformation (Hepburn et al., 2020; Stiglitz, 2019; Stiglitz et al., 2017). Revenues generated from pricing carbon can be reinvested in the energy sector to improve energy efficiency and renewable energy technology. Zakeri et al. (2015) empirically investigated the impact of carbon pricing on emissions reduction, and the results indicated that higher carbon prices tend to reduce emissions due to increased emissions trading costs.

Several studies (Marcantonini & Ellerman, 2015; Pettersson, 2007) have examined the cost of reducing CO_2 emissions by promoting renewable energy. The results indicated that the marginal cost of reducing CO_2 emissions varies significantly across countries. Countries with lower potential for renewable energy and high reliance on fossil fuels in the power sector are inclined to incur higher costs during the transition towards renewable energy. Thus, whether renewable energy will replace fossil fuels depends on technological advancements and economic development levels. The implementation of carbon pricing policies might stimulate renewable energy transition and sustainability by increasing the cost of using fossil fuel energy. This conjecture was supported by a recent study from Dang (2025), who investigated the relationship between fossil fuel prices and energy transition. The results show that rising prices of fossil fuels significantly promote the development of clean energy market.

In light of this exploration, we hypothesise that carbon pricing policies could enhance the development of renewable energy, with effectiveness varying across countries based on economic development and technological advancement levels. To investigate this hypothesis, this study employs an ex-post econometric analysis, combining propensity score matching (PSM) and difference-in-differences (DiD) model to examine the impacts of carbon pricing policies on renewable energy capacity from 2006 to 2022. The study accounts for policy heterogeneity by distinguishing between developing and developed countries and analyses the dynamic treatment effect to capture the persistence of these policies.

Existing literature on carbon pricing policies has primarily focused on their role in mitigating CO_2 emissions, often overlooking their impact on renewable energy development (Hepburn et al., 2020; Liu et al., 2017; Rafaty et al., 2025). This study fills this gap by providing empirical evidence on the influence of carbon pricing policies on renewable energy capacity. Both developing and developed countries are considered separately in renewable energy production analysis, as the effectiveness of carbon pricing policies might be heterogeneous at different levels of economic development (Marcantonini & Ellerman, 2015). Instead of using a single DiD method, a combination of DiD and PSM is adopted to minimise the selection bias and heterogeneity problem. Furthermore, it examines the dynamic change in treatment effect to determine the duration of the impact of carbon pricing policies in regions with varying levels of economic development. Therefore, our study is more comprehensive and provides policymakers with more insights to improve environmental quality.

The rest of our paper is organised as follows: Section 2 briefly provides a summary of the related literature. Section 3 presents the model, data sources and methodology to simulate the impacts of carbon pricing policies on renewable energy capacity. Section 4 shows the empirical results of the study. Section 5 concludes the paper and provides policy implications.

2. Literature Review

Renewable energy plays a vital role in the ongoing transformation of the energy system and sustainable development (Gielen et al., 2019). Past studies (Allen et al., 2016; Gielen, 2017) underscored the importance of energy efficiency and renewable energy technologies to the energy transition. More attention should be paid to the improvement of renewable energy generation, as it not only mitigates climate change by reducing the reliance on fossil fuel energy sources but also leads to sustainable economic development through advancements in green technology. Several factors contribute to the production and diffusion of renewable energy, such as investment in renewable energy, technological innovation, and market competition. The success of these incentives largely depends on effective policies.

Both developing and developed economies have widely used carbon pricing policies to combat the adverse effects of climate change. In a carbon market, polluters pay for the carbon they emit into the atmosphere. This carbon pricing mechanism reduces polluters' incentive to produce carbon-intensive energy and encourages a shift towards renewable energy by increasing the cost of emitting carbon. Carbon-pricing instruments currently cover 23% of global GHG emissions (World Bank, 2023). Existing studies recognise that carbon pricing policies can promote renewable energy and decarbonise economies (Aflaki & Netessine, 2017; Best & Burke, 2018; Liebensteiner & Naumann, 2022). However, studies have yielded varying findings on the impact of carbon pricing on renewable energy generation.

For instance, Bird et al. (2008) examined the effect of carbon regulation on the demand for renewable energy. They argued that well-designed carbon regulations could lead consumers to purchase green power, thereby effectively reducing emission levels. In addition, the European Union's combination of renewable energy targets and Emissions Trading System (ETS) policies in 2005 has been criticised by several studies for potentially leading to higher marginal abatement costs and failing to mitigate CO_2 emissions (Aldy & Pizer, 2009; Fischer & Preonas, 2010; Jonghe et al., 2009). Conversely, Río (2017) explored whether the EU ETS impedes the achievement of the renewable energy target, and the results showed that the EU ETS and the renewable energy sources target are compatible in the long term.

Furthermore, Pietzcker et al. (2021) conducted a scenario analysis to evaluate the effectiveness of the EU ETS on energy transition. They found that more stringent ETS targets could accelerate the energy transformation by 3–17 years. However, by constructing a dynamic recursive computable general equilibrium (CGE) model, Lin and Jia (2020) demonstrated that ETS alone cannot promote renewable energy generation without the government allocating ETS revenue to renewable energy. The consensus from the above studies suggests that the EU ETS is an effective instrument in promoting renewable energy. In developing countries, Dong et al. (2019) assessed the impact of China's national emission trading scheme using a CGE model. Their findings suggest that ETS can promote the deployment of low-carbon technology, with traded carbon decreasing as more renewable energy is used for power generation.

Another type of carbon pricing policy is carbon taxes, which is considered a Pigouvian tax by compensating the difference between marginal private cost and marginal social cost caused by environmental externalities (Pigou, 1920). However, carbon taxes are often criticised for lacking political feasibility and uncertainty for emission mitigation (Kahn & Franceschi, 2006; Wittneben, 2009). While carbon taxes may lower CO_2 emissions, they may not lead to increased investment in renewable energy due to the high cost and the intermittency of renewable energy supply (Kök et al., 2016). Similarly, Aflaki and Netessine (2017) also concluded that the intermittency of renewable energy sources impedes investment in renewable energy capacity. By using game models, their study indicates that although renewable energy sources may become cost-competitive through carbon taxes, high carbon prices may reduce the share of renewable energy capacity in the overall electricity generation system.

On the contrary, Best and Burke (2018) investigated the determinants of solar and wind energy adoption using cross-sectional variation. Their findings suggest that carbon pricing plays a crucial role in the adoption of solar and wind energy. Therefore, the government should implement carbon pricing policies to support renewable energy development. Nevertheless, the feasibility of carbon pricing mechanisms faces significant criticism in developing countries. Factors such as resistance to carbon taxation, consumers' sensitivity to carbon price increases, and income inequality can provoke resistance to carbon pricing in low-income economies (Damert et al., 2017; Finon, 2019). Carbon pricing could exacerbate poverty in lower-middle-income countries, where a large proportion of expenditure is on traditional energy. In addition, upper-class consumers in developing countries, who are major energy consumers, may not be willing to pay for CO_2 emissions. It seems that income could exert a substantively positive influence on driving the transition toward a low-carbon economy. However, countries with high income may not always guarantee the effectiveness of carbon pricing policies. By exploring the impact of income on environmental quality across 99 countries, Masron and Subramaniam (2020) found that in the absence of high-quality institutions, higher income may fail to reduce climate change damage effectively. Therefore, the disparity between developing countries and developed countries should be taken into account when it comes to the effectiveness of carbon pricing policies.

Although carbon pricing is often promoted as a key instrument to combat climate change and support the transition to renewable energy, empirical findings remain inconclusive. Some studies have cast doubt on the universal effectiveness of carbon pricing mechanisms in mitigating climate change and stimulating renewable energy. For example, Yin et al. (2024), employing the panel cross sectionally augmented auto regressive distributed lag (CS-ARDL) model, question the efficacy of carbon taxes in promoting renewable energy. Their findings suggest that carbon taxation may impede renewable energy consumption in the short run, though its effects become positive in the long run. Similarly, Ball (2018) stressed that carbon pricing, while conceptually sound, is often hindered in practice by political constraints. Many jurisdictions impose carbon prices that are either too low or too narrowly scoped to drive meaningful reductions in emissions or to promote renewable energy development. A pertinent example is the European Union Emissions Trading Scheme (EU ETS), which was launched in 2005 as the first large-scale carbon market in the world. During Phase I, however, the scheme suffered from an oversupply of permits, resulting in carbon prices that were sufficient to disincentivise polluting activities (Wang & Paavola, 2023). In the United States, efforts to apply market-based GHG regulation were similarly constrained. Despite the successful use of emission trading under the U.S. Clean Air Act to combat sulphur dioxide, attempts to apply a similar strategy for GHG failed largely due to political opposition, resulting in the continued dominance of non-market, command-and-control approaches (Schmalensee & Stavins, 2013).

Globally, despite the growing adoption of carbon pricing schemes, their actual coverage remains limited. As of World Bank (2025), only about 28% of total GHG emissions are subject to some form of carbon pricing. This limited coverage has led several scholars to argue that the growth of renewable energy has, in practice, been more strongly driven by subsidies and regulatory mandates than by carbon policy instruments. For instance, Shen and Luo (2015) contended that command-and-control measures, including production quotas and subsidies, have played a more decisive role in shaping the renewable energy landscape. The case of Germany provides a telling example. Although the country has witnessed a significant increase in the share of renewable energy in its power mix, this expansion has mainly been financed through public support payments rather than market-based carbon pricing (Liebensteiner & Naumann, 2022). Thus, a growing body of literature suggests that carbon pricing, in its current form, may not be the most effective lever for expanding renewable energy, especially in the absence of complementary policies.

Although previous studies have made valuable attempts to address the impact of carbon pricing policies on renewable energy, their findings remain incomplete and, in some cases, inconclusive – giving rise to several research gaps that this study seeks to fill. First, previous studies tend to examine carbon policy instruments in isolation, focusing on either the ETS or the carbon tax. This narrow scope limits understanding of the relative or combined impact. Our study contributes by jointly evaluating both instruments and their effects on renewable energy capacity. Second, the literature is skewed toward developed countries or single-country analyses, which undermines generalisability. We address this by conducting a cross-country comparison between developed and developing economies, recognising their differing institutional and energy market structures.

Third, prior research has typically assessed renewable energy generation, a variable subject to short-term fluctuations. By contrast, we focus on renewable energy capacity for two reasons: (a) In alignment with the global pledge made at the 28th United Nations Climate Change Conference (United Nations Framework Convention on Climate Change [UNFCCC], 2023), which seeks to triple global installed renewable energy capacity by 2030, we investigate whether carbon pricing policies contribute meaningfully towards achieving that capacity target, and (b) Renewable energy capacity represents the maximum potential power output and serves as a more stable proxy for long-term investment in the sector (Wüstenhagen & Menichetti, 2012). Thus, it serves as a more suitable proxy for capturing investor intentions and behavioural responses to carbon pricing, particularly in terms of commitment to infrastructure expansion and technological adoption.

Finally, a limited number of studies, such as Xu and Yang (2024), have attempted to link carbon pricing directly to renewable energy outcomes, and even fewer have done so using robust causal inference methods that account for policy timing and group-specific heterogeneity. Although earlier works (e.g., Shrimali & Rohra, 2012; Yin & Powers, 2010) analysed the efficacy of climate policies more broadly, they seldom isolate the effects of carbon pricing on renewable capacity. We bridge this methodological gap by applying a propensity score matching (PSM) approach combined with a staggered difference-in-differences (DiD) estimator – commonly referred to as the PSM-DiD method – to more effectively identify the impacts of carbon pricing policies across diverse national contexts. Specifically, this approach allows us to estimate not only the average treatment effects but also the time-varying and group-specific heterogeneous impacts of carbon pricing in both developed and developing economies.

3. Methodology and Data

In the previous section, we reviewed the recent literature on carbon pricing policies and renewable energy. In this section, the model specification, data source and estimation strategies used will be discussed.

3.1 Model Specification

The purpose of this study is to explore the effect of carbon pricing policies on renewable energy capacity from the supply side. Renewable energy capacity is defined as the maximum amount of electric power that a power plant can supply at a specific point in time under certain conditions (U.S. Energy Information Administration [EIA], 2024). To analyse how carbon pricing policies affect renewable energy capacity, we utilise the production function to construct an econometric model. The Cobb-Douglas production function has been widely used in estimating economic production in both macro- and micro-level analysis. Therefore, we adopt the basic Cobb-Douglas functional form in the following format:

$$\mathrm{RE}_{it} = K_{it}{}^{\alpha}(A_{it}L_{it})^{1-\alpha} \tag{1}$$

where RE_{it} is the outcome of renewable energy generation capacity in country i in year t, A_{it} stands for labour augmenting technological progress, K_{it} is capital stock, L_{it} is the labour force. Parameter α should be less than one with the property of diminishing marginal productivity. If the labour force and labour-augmenting technology are enhanced over time, we can assume the following functions to hold:

$$A_{it} = A_{i0}e^{g_i t}Z_{it}^{\theta_i} \tag{2}$$

$$L_{it} = L_{i0}e^{n_i t} \tag{3}$$

where n represents the exogenous rate of growth of the labour force, g_i stands for the exogenous rate of technological progress, t is time, and θ_i betokens the coefficients from the vector of factors specified in Z_{it} namely GDP per capita (lnGDP_{it}), energy security (ES_{it}), urbanisation (URBAN_{it}) and energy consumption per capita (lnEC_{it}). According to empirical studies (e.g., Omri & Nguyen, 2014; Pfeiffer & Mulder, 2013; Sadorsky, 2009a, 2009b; Salim & Rafiq, 2012), per capita GDP is a widely used variable that positively influences renewable energy development. This is because a higher GDP fosters capital investment, which can incentivise renewable energy projects. Other studies (e.g., Aguirre & Ibikunle, 2014; Marques & Fuinhas, 2011) suggest that an increase in energy consumption (or energy intensity) can be supported by both fossil fuel energy sources and renewable energy generation. Consequently, energy consumption may impact renewable energy production, and thus, we control for energy consumption.

In addition, Marques et al. (2010) argued that energy security can promote renewable energy. Efforts to reduce reliance on energy imports are expected to positively impact renewable energy generation. Following Marques et al. (2010), this study includes energy security by using energy import dependency as a proxy. Some studies posit that energy imports are positively related to renewable growth because increased reliance on energy imports necessitates more efforts to enhance renewable energy generation to improve a country's energy security.

Furthermore, an important factor for a sustainable economy is urban resilience (Sharifi & Yamagata, 2016). Renewable energy capacity may be linked to urbanisation development. Therefore, capital stock per capita, GDP per capita, urbanisation, energy security and energy consumption per capita are included as control variables in the model to minimise the omission of variable(s) bias.

Substituting equations (2) and (3) into equation (1), and then applying log transforming on both sides of equation (1) yields the following linear per capita output form:

$$\mathrm{lnRE}_{it} = \alpha + \gamma\mathrm{ln}k_{it} + \varphi\mathrm{lnGDP}_{it} + \eta\mathrm{URBAN}_{it} + \psi\mathrm{ES}_{it} + \theta\mathrm{lnEC}_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{4}$$

where ln represents the natural logarithm, μ_i and τ_t are the country- and time-specific effect variables, respectively, and ε_{it} is the error term.

3.2 Sources of Data and Summary of Descriptive Statistics

The purpose of this study is to investigate the effect of carbon pricing policies (ETS and carbon tax) on renewable energy generation capacity in countries with different levels of development. To achieve this, developing and developed countries are discussed separately using balanced panel data of 62 countries selected from the International Energy Agency (IEA). The dataset includes 21 developed countries and 18 developing countries in the treatment group, which have officially adopted carbon pricing policies through specific legislation and regulations, and 23 countries in the control group, which have not confirmed carbon pricing policies. This dataset covers the period from 2006 to 2022.

Table 1 lists the countries in the sample, including the treatment group and control group. The data are collected from various reputable databases. Specifically, the dataset for renewable energy generation capacity, measured in megawatts (MW) is collected from *Renewable Energy Statistics* released by the International Renewable Energy Agency (IRENA). Energy security, defined as the share of net energy imports

Table 1. Countries of the treatment group and the control group

Treatment group				Control group
Developed countries	Year of implementation	Developing countries	Year of implementation	
Austria	2022	Argentina	2018	Albania
Canada	2019	Chile	2017	Australia
Czech Republic	2006	China	2021	Botswana
Denmark	1992	Colombia	2018	Bosnia & Herzegovina
Estonia	2000	Egypt	2022	Brazil
France	2014	India	2022	Brunei Darussalam
Germany	2021	Indonesia	2022	Cote d'Ivoire
Greece	2005	Kazakhstan	2013	Gabon
Hungary	2015	Latvia	2004	Georgia
Iceland	2010	Mexico	2014 & 2022	Israel
Ireland	2010	Montenegro	2022	Kenya
Japan	2012	Singapore	2019	Malaysia
Korea	2015	South Africa	2019	Moldova
Lithuania	2015	Sri Lanka	2016	Morocco
Luxembourg	2021	Ukraine	2011	Nigeria
New Zealand	2008	Uruguay	2022	Pakistan
Portugal	2015	Vietnam	2022	Senegal
Spain	2014			Serbia
Switzerland	2008			Slovak Republic
The Netherlands	2015			Thailand
United Kingdom	2013			Turkey
				United States
				Vietnam

Note: The classification of countries in this study is based on the *World Situation and Prospects 2014* (United Nations, 2014).

Table 2. Summary of descriptive statistics

Variables	Obs.	Mean	Std. dev.	Min	Max
Treatment group – developing countries					
lnRE	306	8.444	2.046	2.485	13.965
ln*k*	306	24.845	1.726	20.294	29.797
lnGDP	306	9.078	0.773	7.173	11.324
URBAN	306	73.136	16.130	43.868	100.000
lnEC	306	9.922	0.847	7.404	12.013
ES	306	5.201	3.591	0.335	15.924
Treatment group – developed countries					
lnRE	357	9.029	1.618	3.871	11.908
ln*k*	357	25.166	1.563	21.371	28.040
lnGDP	357	10.672	0.522	9.109	11.803
URBAN	357	78.880	11.064	57.115	98.153
lnEC	357	10.869	0.455	10.130	12.146
ES	357	8.925	3.864	2.990	25.768
Control group					
lnRE	391	8.425	1.890	2.773	12.770
ln*k*	391	24.419	1.972	20.833	29.240
lnGDP	391	8.864	1.309	6.550	11.244
URBAN	391	58.144	19.014	22.045	92.886
lnEC	391	9.733	1.057	7.279	11.401
ES	391	5.144	4.650	0.200	19.741
Total sample					
lnRE	1054	8.635	1.871	2.485	13.965
ln*k*	1054	24.796	1.797	20.294	29.697
lnGDP	1054	9.539	1.251	6.550	11.803
URBAN	1054	69.520	18.227	22.045	100.000
lnEC	1054	10.173	0.973	7.279	12.146
ES	1054	6.461	4.477	0.200	25.768

of gross available energy, is obtained from *World Energy Balances* by the IEA. Energy consumption per capita is collected from *Enerdata*. We obtain data on per capita real GDP, urbanisation and the per capita real gross fixed capital formation from the *World Development Indicators* (WDI). Data on the timing (dates) of carbon pricing policies are extracted from the *State and Trends of Carbon Pricing Dashboard* provided by the World Bank. We include both the ETS and carbon taxes as indicators for determining the carbon pricing policies. In addition, we account for countries that have implemented both ETS and carbon taxes in different years. Since the carbon pricing policy is represented by a binary variable in our estimation framework, we use the earliest year of implementation, whether for the ETS or the carbon tax, as the starting point of policy adoption. This approach ensures that the estimated policy effect accurately reflects the initial introduction of carbon pricing in each country. The descriptive statistics of all the variables are shown in Table 2.

3.3 Estimation Strategies

In this study, we explore the effect of the carbon pricing policies on renewable energy capacity, considering the implementation of these policies as a quasi-natural experiment. A difference-in-differences method provides a straightforward way to measure the first difference within the treatment group before and after the policy implementation, as well as the second difference between the treatment group and the control group. In this contest, the control group comprises countries that have not experienced any policy changes, whereas the treatment group consists of countries that have undergone carbon pricing policy changes.

Given the variation in the timing of carbon pricing policy implementation across countries, and the potential heterogeneous effects at different levels of economic development, we employ a staggered DiD model to discuss the impact of carbon pricing policies on renewable energy generation capacity in both developing and developed countries. Accordingly, we specify the following DiD model of renewable energy generation:

$$\begin{aligned}\ln\mathrm{RE}_{it} = {} & \alpha + \beta(\mathrm{Treat}_i \times \mathrm{CPP}_t) + \gamma\ln\mathrm{k}_{it} + \varphi\ln\mathrm{GDP}_{it} + \eta\mathrm{URBAN}_{it} + \psi\mathrm{ES}_{it} + \\ & \theta\ln\mathrm{EC}_{it} + \mu_i + \tau_t + \varepsilon_{it}\end{aligned} \tag{5}$$

where Treat_i is a dummy variable that equals 1 if country i is in the treatment group and 0 if country i is in the control group. CPP_t is a dummy variable that equals 1 for a country before the implementation of carbon pricing policies and 0 otherwise. μ_i and τ_t are the country- and time-specific effect variables, respectively, and ε_{it} is the error term.

($\mathrm{Treat}_i \times \mathrm{CPP}_t$) is the interaction between the treatment group and the timing of the implementation. *it* equals 1 in the years after country *i* implements carbon pricing policies and 0 otherwise. The coefficient β is the estimated average treatment effect on the treated (ATET), indicating the extent to which renewable energy generation capacity is attributed to carbon pricing policies. If β is positive, it suggests that carbon pricing effectively encourages the generation of renewable energy. If β is negative, it indicates that carbon pricing is an ineffective tool for decarbonisation as renewable energy generation tends to be low.

Two fundamental assumptions are required to ensure that the results of the DiD method are plausible (Dehejia, 2005). First, the parallel trend assumption, which states that the control group should reflect the situation that the treatment group has not implemented the policy. Recent studies (e.g., Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Wooldridge, 2005) demonstrate that two-way fixed effects regressions provide unbiased estimation results for the average treatment effect if the parallel trend holds. However, a systematic difference between the two groups could lead to sample selection bias.

Second, randomised group assignment assumes that all observations are randomly selected, which is often not the case in applied research. In practice, inconsistencies in classification criteria and non-random sample selection can compromise the validity of comparisons between treatment and control groups. In this study, the adoption of carbon pricing policies, whether through emissions ETS or carbon tax, is determined by government decisions and prevailing economic conditions. As such, countries in the treatment group and control group, particularly when distinguishing between developed and developing economies, may differ systematically in ways that introduce selection bias. These underlying differences may violate the parallel trends assumption required for conventional DiD estimation. To address this concern, Rosenbaum and Rubin (1984) introduced the propensity score matching (PSM) method, which allows for the construction of a counterfactual group by matching the control group to the treatment group based on similar observable characteristics. This method estimates the propensity score for each sample and selects the control group samples that are closest in score to those in the treatment group (Zang et al. 2020).

The PSM-DiD model was first introduced by Heckman et al. (1998). The combination of PSM and DiD can improve estimation accuracy and effectively address the endogeneity problem and sample selection bias (Heckman et al., 1998; Smith & Todd, 2005;). Therefore, the parallel trends assumption could be satisfied. This study accounts for heterogeneity of treatment and control groups. It adopts the PSM-DID method to accurately estimate the impact of carbon pricing policies in developing and developed countries. The PSM method comprises two steps. First, assuming country *i* is from the treatment group, country *j* is from the control group, we include all the control variables, such as human capital, urbanisation, energy consumption and energy security as covariates. Given the covariates *x*, we calculate the conditional probability of country *i* or *j* entering the treatment group implementing carbon pricing policies.

$$\text{logit}(\rho_i) = \log\left(\frac{\rho_i}{1-\rho_i}\right) = \beta_0 + \sum \beta_i \chi_i + \varepsilon_i \tag{6}$$

$$\rho_i = \rho(\text{Treat}_i = 1 \mid \chi = \chi_i) \tag{7}$$

$$\hat{\rho}_i = \sum \hat{\beta} \chi_i + \hat{\beta}_0 \tag{8}$$

where ρ_i is the probability that the country *i* is assigned to the treatment group under the condition of a series of covariates χ_i. The logit model is used to estimate the parameter ρ_i. logit(ρ_i) = 1 when the country *i* is the treatment group, 0 otherwise. The estimated value of parameter $\hat{\beta}_0$ and $\hat{\beta}\chi_i$ could be obtained through binary logit regression on equation (6). The propensity score $\hat{\rho}_i$ can be calculated through the estimated parameter values based on equation (8). Second, we use the kernel matching method to find countries with similar propensity scores that have adopted carbon pricing policies, serving as the new control group.

4. Empirical Results

In this section, we use the PSM-DiD method to explore the treatment effect of implementing carbon pricing policies and to determine whether these policies stimulate renewable energy capacity. Several preliminary tests are conducted to ensure the correct selection of the sample and model. The parallel trend assumption is tested to identify any differences between the treatment group and the control group. To improve estimation accuracy, the PSM method is used to overcome the self-selection problem of the sample. A Hausman test is performed to decide whether to use a fixed effect model or a random effect model.

We estimate the average treatment effect of carbon pricing policies using a staggered DiD model to capture the different timing of policy implementation across countries. Additionally, the dynamic treatment effect is analysed to explore the persistence of carbon pricing policies.

4.1 Test of the Parallel Trend

The parallel trends assumption is an important requirement to accurately estimate the effects of carbon pricing policies using DiD estimation. This assumption requires that, before the implementation of carbon pricing policies, the treatment group and control group should exhibit similar trends in renewable energy capacity. Suppose a different trend exists between these groups before policy implementation; the variation in renewable energy capacity between the two groups is likely to be heterogeneous.

This study tests the parallel trends by regressing the renewable energy capacity on the interaction between the treatment group and the time dummy variable from four years before the implementation to one year after the implementation. This method examines whether the sample selection is plausible for our estimation. The parallel trend assumption is satisfied if the estimated coefficients of carbon pricing and the F-statistics for parallel trends are statistically insignificant. Table 3 presents the coefficient estimates of parallel trends and diagnostic tests. The F-statistics for parallel trends in Table 3 are statistically significant, indicating that there are significant differences in renewable energy capacity between treatment and control groups for developing and developed countries before the implementation of carbon pricing policies.

Specifically, in developing countries, the estimated coefficients are statistically significantly different from zero (0.394 and –0.666) in the two years and one year before the implementation of carbon pricing policies; in developed countries, the renewable energy capacity of the treatment group and the control group is heterogeneous (–0.208 and 0.134) in the four years and one year before carbon pricing policies. These results imply that selected treatment and control groups fail to follow the same trend, resulting in the violation of the parallel trend assumption, as well as a selection bias problem. Therefore, we drop countries that fail to meet the parallel trend assumption, and then use the PSM method to test whether the remaining sample countries are suitable for further DiD analysis (Fu et al., 2021; Uchida et al., 2007).

4.2 Results of the PSM Test

In this section, the PSM method is used as a more effective approach for selecting the appropriate control group than self-selection (Caliendo & Kopening, 2008; Dehejia & Wahba, 2002). Figure 1 and Figure 2 depict the differences in the distribution of the propensity scores. The results indicate that, for both developing and developed countries, there is a substantial distribution difference in propensity scores between the treatment group and the control group before matching samples. This suggests that non-random sample selection leads to selection bias and heterogeneity issues.

After matching, the trends of the propensity scores for these two groups become almost consistent, and the differences between them are significantly reduced, indicating that the matched samples satisfy the parallel trends assumption. This finding demonstrates the reliability of the PSM method. Based on these results, the matched samples will be selected to conduct PSM-DiD analysis.

Table 3. Results of the parallel trend test for developing and developed countries

Variables	Developing countries	Developed countries
Carbon pricing-F4	0.042	–0.208*
	(0.130)	(0.114)
Carbon pricing-F3	0.082	0.096
	(0.167)	(0.114)
Carbon pricing-F2	0.394***	–0.052
	(0.107)	(0.102)
Carbon pricing-F1	–0.666***	0.134*
	(0.175)	(0.065)
Carbon pricing	–0.344**	0.572***
	(0.123)	(0.106)
Carbon pricing-L1	0.538***	–0.202**
	(0.081)	(0.083)
Capital stock	0.814***	0.882***
	(0.018)	(0.006)
GDP	0.576***	–0.308***
	(0.077)	(0.347)
Energy security	0.017*	0.119***
	(0.009)	(0.011)
Urbanisation	–0.014***	0.012***
	(0.002)	(0.002)
Energy consumption	–0.421***	–0.019
	(0.048)	(0.024)
Diagnostic tests		
Adjusted R^2	0.679	0.776
F-statistics for parallel trend	16.56***	5.21***
p-values	0.000	0.007
Observations	612	663
Conclusion for parallel trend	Rejected	Rejected

Notes: This table presents the results of parallel trend tests for the staggered DiD model. Carbon pricing-F1 is the interaction items equals one for one year before the occurrence of the carbon pricing policies, zero otherwise. Carbon pricing-F2, Carbon pricing-F3 and Carbon pricing-F4 follow the same patterns. Carbon pricing-L1 is the interaction items equals one for one year after the occurrence of the carbon pricing policies. Values in parenthese ( ) denote the robust standard errors clustered at the country level. *, ** and *** indicate statistically significant at the 10%, 5% and 1% levels, respectively.

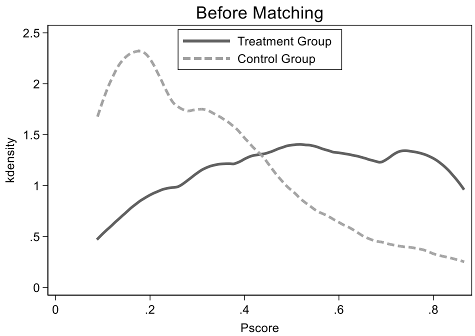

Figure 1(a)

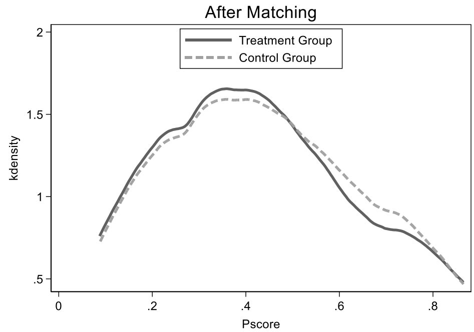

Figure 1(b)

Figure 1. Kernel density distribution of propensity matching score in developing countries

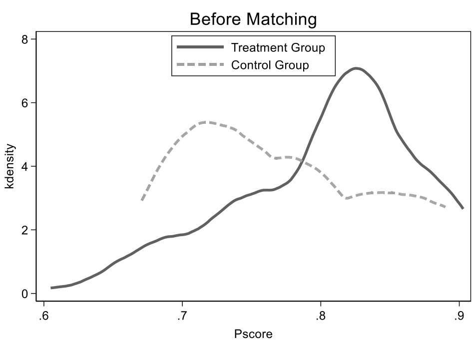

Figure 2(a)

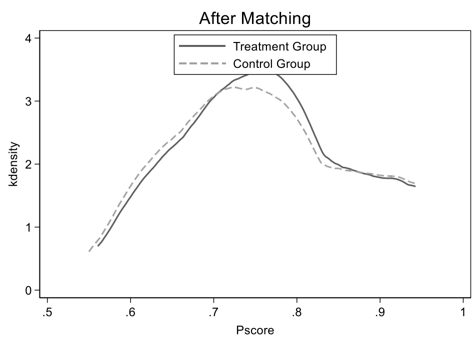

Figure 2(b)

Figure 2. Kernel density distribution of propensity matching score in developed countries

4.3 PSM-DiD Analysis

Given the discussion in Section 4.2, we adopt the PSM-DiD method for the empirical estimation. A Hausman test is conducted to determine whether to use a fixed effect model or a random effect model. As shown in Table 4, the fixed effect model outperforms the random effect model. Therefore, we control for country- and time-specific effects in the estimation.

Table 4. Specification tests

Tests	Developing countries		Developed countries	
	Statistics	*p*-values	Statistics	*p*-values
Hausman test	73.82***	0.000	41.28***	0.000
Wooldridge test	580.82***	0.000	49.34***	0.000

Note: *** indicates statistically significant at the 1% level.

With the matched samples, the estimated results of the PSM-DiD estimation are presented in Table 5. This study introduces several control variables gradually to test the robustness of the treatment effect. Columns (1) to (5) in Table 5 show the effect of carbon pricing policies on renewable energy capacity in developing countries, the coefficient of ($Treat_i \times CPP_t$) is positive and statistically significant. The estimated coefficients of carbon pricing policies in these five models range from 0.12 to 0.184 at the 10% significance level, indicating that renewable energy capacity in developing countries can be stimulated by implementing carbon pricing policies. This finding aligns with some existing literature (Pietzcker et al., 2021; Río, 2017).

These results suggest that governments in developing countries need to establish mature carbon pricing policies such as comprehensive emission trading systems and appropriate carbon taxes. Although many developing countries have set renewable energy targets, the energy transition faces challenges such as a lack of renewable energy investment and high production costs. The results imply that carbon pricing policies effectively stimulate the energy transition in developing countries. On one hand, these policies increase the cost of producing fossil fuel energy, prompting fossil fuel energy suppliers to shift towards renewable energy. On the other hand, revenues from carbon charges could be invested in renewable energy technology innovation. Overall, based on our findings, carbon pricing policies play a key role in promoting renewable energy capacity in developing countries.

In Columns (6) to (10) in Table 5, we present the empirical results for developed countries. The coefficients of ($Treat_i \times CPP_t$) are negative and statistically significant at the 5% level. Instead of promoting renewable energy capacity, the implementation of carbon pricing policies reduces renewable energy capacity by 14.4% in developed countries. This result is consistent with the earlier studies of Aflaki and Netessine (2017) and Kök et al. (2016), suggesting that the high cost of carbon pricing and the intermittency of renewable energy sources hinder investment in renewable energy, thereby reducing renewable energy capacity in developed countries. Another plausible explanation relates to windfall profits and path dependence. Fossil fuel prices have surged in recent years due to rising global energy demand and the Russian invasion of Ukraine (IEA, 2025). Over 80% of the top 100 global energy companies are based in developed countries, which helps explain why windfall profits are predominantly captured by firms in these regions (Thomson Reuters, 2018). A recent study examining 93 of the world's largest oil and gas companies in 2022 reported a combined total of US$490 billion of windfall profits (Egli et al., 2024). These high profits from fossil fuel activities impede the transition towards renewable energy, as the path dependence of fossil fuel technologies constrains innovation in renewable energy.

In addition, carbon pricing policies – first introduced in developed countries such as Finland and Norway – were initially set at levels too low to internalise the environmental costs of carbon emissions (Tvinnereim & Mehling, 2018). In other words, early-stage carbon pricing policies lacked stringency and proved ineffective, partly because policymakers had limited awareness of the true social cost of carbon emissions compared to producers. The failure of early carbon pricing regimes may have led investors and producers to underestimate or disregard the cost of emissions.

Table 5. Results of the PSM-DID analysis

	Developing countries					Developed countries				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	2.988 (2.383)	1.162 (2.000)	1.097 (2.087)	0.133 (1.774)	–6.654** (2.880)	3.779 (2.870)	5.825 (3.724)	5.627 (3.623)	5.484 (4.283)	10.512* (5.384)
Carbon pricing	0.145* (0.078)	0.120 (0.075)	0.138* (0.075)	0.184 ** (0.076)	0.139 * (0.075)	–0.131** (0.059)	–0.136** (0.058)	–0.144** (0.060)	–0.144** (0.060)	–0.144** (0.060)
Capital stock	0.236** (0.096)	0.134 (0.085)	0.162* (0.082)	0.132* (0.078)	0.188** (0.080)	0.222* (0.113)	0.232** (0.113)	0.253* (0.114)	0.253** (0.114)	0.247** (0.113)
GDP	–	0.478*** (0.124)	0.426*** (0.126)	0.339*** (0.116)	0.079 (0.140)	–	–0.219 (0.196)	–0.232 (0.191)	–0.226 (0.206)	–0.157 (0.214)
Energy security	–	–	–0.106*** (0.039)	–0.151*** (0.038)	–0.143*** (0.036)	–	–	–0.140* (0.073)	–0.141* (0.077)	–0.147* (0.077)
Urbanisation	–	–	–	0.038*** (0.011)	0.028*** (0.011)	–	–	–	0.001 (0.017)	0.002 (0.016)
Energy consumption	–	–	–	–	0.842*** (0.264)	–	–	–	–	–0.526 (0.357)
Diagnostic tests										
Adjusted R^2	0.986	0.986	0.986	0.987	0.989	0.985	0.985	0.986	0.986	0.986
Observations	251	251	251	251	251	171	171	171	171	171

Notes: Capital stock, GDP and energy use are in natural logarithm form to weaken heteroskedasticity. Robust standard errors are clustered at the country level and reported in parentheses. *, ** and *** indicate statistically significant at the 10%, 5% and 1% levels, respectively.

This, in turn, helps explain why such policies in developed countries failed to promote renewable energy capacity significantly.

Conversely, most developing countries have less stable financial systems and economic foundations (Greenwald & Stiglitz, 2006), compelling them to adopt a more cautious approach to carbon pricing policy. As many of these countries implemented carbon pricing policies only after the 2015 Paris Agreement, they may have drawn lessons from the shortcomings observed in early adopters, thereby making their schemes more effective. Finally, Egli et al. (2024) also stressed that the scale of windfall profits from fossil fuel sectors could be sufficient to finance climate-related payments. Therefore, greater government support is needed to accelerate the transition towards renewable energy. Carbon pricing policies alone are insufficient to combat the challenges of climate change. A more comprehensive policy mix – comprising both market-based and non-market-based instruments – is essential to achieving net-zero emissions and sustainable development.

4.4 Dynamic Effects Analysis of Carbon Pricing Policies in Developing Countries

Figure 3 tracks the long-term dynamic treatment effects of carbon pricing policies on stimulating renewable energy capacity in developing countries. The horizontal axis represents the length of exposure, while the vertical axis shows the coefficients of dynamic treatment across exposure duration. The dashed line provides point estimates at 95% confidence intervals for post-treatment periods, allowing for clustering at the national level.

The estimated treatment effects indicate that the positive contribution of carbon pricing policies on renewable energy capacity becomes significantly different from zero in the second year after policy implementation. Additionally, statistically significant

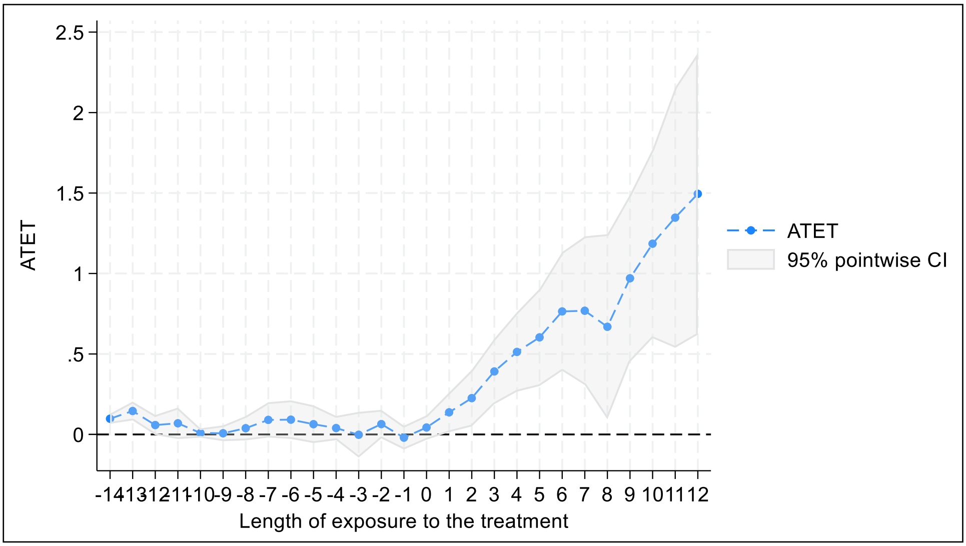

Figure 3. Dynamic effects of carbon pricing policies in developing countries

treatment effects are observed in all post-periods, suggesting that the impact of carbon pricing policies persists in the long term. These results suggest that carbon pricing policies are an effective strategy for developing countries to improve their renewable energy capacity, with effects that could last for an extended period.

5. Conclusions and Policy Implications

In this study, we investigate the effectiveness of carbon pricing policies on renewable energy capacity in developing and developed countries using the PSM-DiD method. The results indicate a positive and significant impact of carbon pricing policies on renewable energy capacity in developing countries. This positive effect becomes more pronounced in the long run, demonstrating that carbon pricing policies effectively stimulate renewable energy capacity. Conversely, for developed countries, we observe a negative and significant impact, suggesting that the implementation of carbon pricing policies reduces renewable energy capacity.

Renewable energy offers an opportunity to achieve sustainable development goals. Therefore, implementing carbon pricing policies enhances sustainability by increasing renewable energy production. However, the effectiveness of these policies varies significantly between developing and developed countries. As carbon pricing mechanisms in developing countries are in their early stages, policymakers in these countries need to establish more mature carbon pricing policies to increase the cost of emitting carbon. Additionally, revenues generated from carbon pricing should be reallocated to support the development of renewable energy by investing in renewable energy technology.

This study also provides empirical evidence that carbon pricing policies in developed countries may not be effective tools in promoting renewable energy development. Moreover, carbon pricing policies alone are not enough to push forward the energy transition. Given the importance of carbon pricing policies and renewable energy, further research should focus on how different types of carbon pricing policies influence renewable energy development at the national level. Furthermore, to accelerate the achievement of renewable energy targets set out by most developed countries, factors that stimulate renewable energy capacity should be further investigated.

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