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Convergence or Divergence? Emission Performance in the Regional Comprehensive Economic Partnership Countries

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Abstract: Emission convergence is a fundamental ground for cooperative CO₂ emission mitigation. We investigate the emission convergence in the Regional Comprehensive Economic Partnership (RCEP) countries using a modified dynamic β -convergence model. From 2000 to 2017, the per capita emissions of the RCEP countries and its subgroups show a statistically significant diverging pattern. Nonetheless, upon accounting for multiple inputs and outputs using data envelopment analysis, we find that two out of the three emission performance indicators show statistically significant absolute convergence. The carbon emission efficiency (*CEE*) of the 15 RCEP countries grew from 0.5719 in 2000 to 0.6725 in 2017 and will converge at a value of 0.8187, while the carbon–population performance (*CPP*) increases from 0.4534 to 0.5690 and will converge at 0.7831. Furthermore, using a conditional β -convergence model, we find that trade volume has no significant effect on the growth rates of *CEE* and *CPP*, but can accelerate their speed of convergence, which indicates that the establishment of the RCEP may facilitate the convergence of its 15 member countries on *CEE* and *CPP*. Our findings suggest that emission mitigation agreement in the RCEP countries is feasible. *CEE*- or *CPP*-based indicators can be used for emission budget allocation.

Keywords: Regional Comprehensive Economic Partnership; carbon emission convergence; data envelopment analysis; dynamic β -convergence; emission efficiency



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1. Introduction

The Regional Comprehensive Economic Partnership (RCEP), a free-trade agreement signed in 2020 by 15 Asia-Pacific countries, accounts for more than 30% of the world's population and 29% of the gross world product. It has been attracting increasing interest in its potential impact on global trade flows as well as the ongoing battle against climate change. Regarding its impact on economies, Petri and Plummer [1] estimated that the RCEP may add USD 186 billion in economic benefits to the global economy by 2030. On its impact in climate change mitigation, Kalirajan and Liu [2] suggested that the RCEP may promote the regional flow of renewable energy trade, thus facilitating the fulfillment of its member countries' climate targets.

Notably, the RCEP has provided many channels to promote commodity trade, to facilitate investment, and to protect intellectual properties, among others. However, it has thus far neglected some burning issues, including environmental standards and climatic cooperation. Meanwhile, regional or global cooperative emission mitigation seems to be emerging as a new normal in overcoming climate change. In this context, a collection of climatic actions by the RCEP member countries has already been under intense discussion. For example, Australia, China, New Zealand, South Korea, and Japan have established their domestic carbon emission trading system [3]; Australia and China launched a joint expert group in 2013 to explore the possibility of linking carbon trading markets [4]; some other member countries have set ambitious climate targets—China, Japan, and South Korea have successively pledged their carbon-neutrality target—and are proactively seeking

multilateral climatic cooperation. Multilateral climatic cooperation is also advancing worldwide: An EU-wide emission trading system has been in effect for a decade and has been proven to be economically efficient in emission mitigation [5]. California and Quebec's carbon markets have been connected since 2014 [6]. Nordhaus [7] appealed for the building of climate clubs to more effectively curb the surging greenhouse gas emissions. Several studies have been conducted to appraise the possibility and potential gains of climatic cooperation in the RCEP countries, for example, Chang and Li [8] studied carbon pricing in the Association of Southeast Asian Nations (ASEANs), a core regional cooperation organization in the RCEP agreement, and established that an aggressive carbon price in the region may significantly enhance regional energy market integration and promote carbon emission reduction. Based on the tremendous economic and emission scales of RCEP members, there should be a growing interest in the feasibility of cooperative emission reduction in the RCEP countries.

A fundamental question in negotiations of climatic cooperation is whether emission performance of participating countries and regions will converge over time. If countries' carbon emissions follow a certain growth pattern and will eventually converge to an equilibrium level, then cooperative carbon mitigation through carbon quota allocations is feasible. Otherwise, climatic cooperation, such as a regional integrated carbon emission market, may lead to a substantial transfer of emission rents through emission trading or the relocation of emission intensive industries [9], thereby resulting in big winners and losers in climatic cooperation and making the cooperation unsustainable. Owing to this reason, the Kyoto Protocol has, for example, excluded developing countries from binding abatement commitments.

Particular interest has been given to the convergence of per capita emissions owing to its intuitive appeal to fairness [10]. The empirical evidence of per capita emission convergence is mixed: Most suggest a lack of evidence that per capita emission converges at the global scales [11,12] or in underdeveloped countries [11], while some suggest that a globally or regionally converging process exists [11,13], such as those in the Organization for Economic Co-operation and Development (OECD) countries. Furthermore, the per capita emission approach has been criticized for neglecting some structural characteristics—it considers solely population as a carbon dioxide (CO₂) emission driving factor but completely ignores other socioeconomic factors that may affect emission convergence [14]. To tackle the issue, some researchers have developed inclusive eco-efficiency indicators to provide a more comprehensive description of emission convergence. Chen et al. [15] developed an energy–carbon performance index and show its convergence in China's construction industry. Sheng et al. [16] found a similar pattern of convergence for pollutant emission performance indices. Li and Lin [17] developed an energy efficiency index and examine the impact of its convergence on China's regional GDP growth. Yet, this literature has barely paid attention to emission convergence in countries other than China. Hence, the emission evolution pattern of the RCEP countries remains unknown.

With the establishment of the RCEP arrangement, there is an urgent need to study the emission convergence and evaluate the possibility of climatic cooperation along this agreement. This study contributes to the literature by investigating the convergence of the RCEP member countries. First, the convergence of per capita emissions is investigated, which is a conventional way to study regional emission convergence [10]. In addition, as the per capita emission approach may overlook some driving factors of CO₂ emissions, the data envelopment analysis (DEA) model, a multi-input multi-output performance evaluation model [18], is adopted to develop inclusive emission performance indices to fully account for the structural characteristics of carbon emissions. Moreover, the effect of trade on the convergence of emission performance is examined in light of the potential trade uptake by the RCEP arrangement.

2. Methods and Data

2.1. Convergence Analysis

The convergence model first appeared in Solow's neoclassical growth model, which suggested the existence of the catch-up effect—underdeveloped regions show a systematically faster economic growth rate than developed regions such that the regional development disparity will eventually vanish [19]. To test this assumption, different methodologies have been developed. Widely adopted approaches are β -convergence, σ -convergence, and stochastic convergence. We focus exclusively on the β -convergence approach owing to two reasons: First, it has an intuitive appeal to the “catch-up” effect. That is, it tests if underdeveloped countries experience a systematically higher growth rate, β , compared with developed countries. Second, β -convergence is capable of providing additional information about convergence speed and equilibrium emission level [12].

The β -convergence approach can be further classified into: (1) absolute convergence [12] and (2) conditional convergence [20]. Absolute convergence indicates that all the countries follow an identical path and converge toward a globally same level regardless of the countries' economic, social, and political statuses. In its specification, the only explanatory variable is countries' past emission performances, i.e., the lagged level of per capita emissions. On the contrary, conditional convergence considers other country-specific variables that may influence the converging process, which suggests that countries with varying characteristics may converge to different local states. The original β -convergence model, according to Baumol [19], adopted the following absolute convergence form:

$$\frac{1}{T} \left[\ln \left(\frac{EI_{i,t+T}}{EI_{i,t}} \right) \right] = \alpha - \frac{1}{T} (1 - e^{-\beta T}) \ln EI_{i,t} + \delta_i + \varepsilon_{i,t} \quad (1)$$

where t denotes the starting period, and T denotes the end period; i denotes a country or region; EI denotes an emission indicator, such as per capita emission; α is the constant term related to equilibrium speed; β is the convergence speed—a significant positive/negative β indicates the existence of absolute convergence/divergence in the spatial region; δ_i is country-specific fixed effect that influences the equilibrium level, which can be derived from a fixed-effect model; and $\varepsilon_{i,t}$ is the stochastic error term with a normal distribution of zero mean and constant variance. The original β -convergence model uses only cross-section data, which may lead to biased estimates due to the existence of unknown yearly shocks. Therefore, we reconstructed the model into the following dynamic form, which can more accurately reflect the converging process in a panel data setting:

$$\ln \left(\frac{EI_{i,t}}{EI_{i,t-1}} \right) = \alpha - (1 - e^{-\beta}) \ln EI_{i,t-1} + \delta_i + \varepsilon_{i,t} \quad (2)$$

where, if β is positive, $-(1 - e^{-\beta})$ is negative, which indicates observations in the sample is converging; otherwise, if β is negative, the emission level of different countries is diverging. The model can then be further converted to:

$$\ln EI_{i,t} = \alpha + e^{-\beta} \ln EI_{i,t-1} + \delta_i + \varepsilon_{i,t} \quad (3)$$

The equilibrium level of an emission indicator, or the emission level to which all countries will converge, EI_{eq} , and the converging speed (the time period required by countries with lower level of emission to catch up with that of leading countries), C_T , can be derived as follows [12]:

$$EI_{eq} = e^{\frac{\alpha}{1-e^{-\beta}}} \quad (4)$$

$$C_T = \ln \frac{2}{\beta} \quad (5)$$

As the lagged term, $EI_{i,t-1}$, exists as an independent variable in the right-hand side of the model (3), a correlation between the independent variable and the error term ensues.

Least square estimates or standard fixed effects models usually lead to a biased estimate of β and are thereby inapplicable in this case [21]. A widely used approach to solve the endogeneity problem with the term $EL_{i,t-1}$ is the generalized method of moments (GMM) with instrumental variables. However, Judson and Owen [21] note that the approach fits better with “small T , large N ” problems, which contrasts with the 15×18 sample structure in this paper. They prove that the Anderson–Hsiao (AH) estimates, a loose, restricted GMM-style approach, can provide less unbiased estimates of the “similar T and N ” problem. Therefore, the AH estimates are adopted in this study to address the endogeneity of the lagged term, $\ln EL_{i,t-1}$, in the dynamic β -convergence model. We perform a first-difference approach on model (3) to generate the following:

$$\Delta(\ln EL_{i,t}) = e^{-\beta} \Delta(\ln EL_{i,t-1}) + \Delta(\varepsilon_{i,t}) \quad (6)$$

The endogeneity test suggests that the difference does not eliminate the correlation between $\Delta(\ln EL_{i,t-1})$ and $\Delta(\varepsilon_{i,t})$, thus we need further instrumented $\Delta(\ln EL_{i,t-1})$. There are a variety of ways to deal with endogenous independent variables using instrumental variables. A common instrumental variable modelling practice is the two-stage least squares method. A key issue in the two-stage least squares method is the selection of instrumental variables. Previous literature used to adopt physical variables as instrumental variables in the modelling, such as wind speed, country size, inter-country proximity, and the like [22–24]. These instrumental approaches are often adopted in a cross-sectional setting. They do not tackle serial correlation in a time-series or a panel data setting, which is often the case in long-run growth models [21]. To deal with this, Anderson and Hsiao [25] recommended to instrument the endogenous variable, i.e., $\Delta(\ln EL_{i,t-1})$, with either a lagged difference or a lagged level. Arellano and Bond [26] demonstrate the superiority of the lagged level over the lagged difference in terms of the estimation efficiency. Thus, we adopt $\ln EL_{i,t-2}$ as an instrumental variable for $\Delta(\ln EL_{i,t-1})$ in this study. The first stage F -statistic is used to examine the consistency of adopting the two-period lagged term as an instrumental variable. Since only one instrumental variable is adopted for one endogenous variable, there is no issue with over-identification. Thereby, no over-identification test is conducted.

Furthermore, we can consider influencing factors vis-à-vis countries’ convergence behavior, which presents the conditional convergence model:

$$\ln\left(\frac{EL_{i,t}}{EL_{i,t-1}}\right) = \alpha - (1 - e^{-\beta}) \ln EL_{i,t-1} + \gamma \ln(x_{i,t}) + \delta_i + \varepsilon_{i,t} \quad (7)$$

where denotes control variables for a conditional convergence analysis. There may exist numerous conditions that the converging process depends on, such as foreign investment, financial development, and the like [27]. In the context of the RCEP agreement, we are particularly interested in the effect of trade on emission convergence. Trade may induce technology transfer and knowledge spillover, therefore accelerating the converging process. Especially, there may exist a learning-by-exporting effect, where pollution-heavy countries improve their production technology through exporting products to low-pollution countries. It may also induce polluting industry relocation, where pollution-intensive industries shift from high-income to low-income countries. High-income countries subsequently import “dirty” commodities with high CO₂ emissions from low-income countries [28,29]. Thereby, this international specialization may keep or even enlarge the gaps among countries. Given the mixed evidence, we conditioned convergence on export volume (EX) and study how it may affect emission convergence of RCEP countries. We can investigate if RCEP countries’ emission performances may converge to a local steady state, the level of which depends on the trade volume of a country.

2.2. Emission Performance Index

The per capita emission approach may ignore some structural characteristics, leading to biased estimation. Hence, we propose emission performance measurements based on the DEA model. This approach has been widely used in composite indicator design for multi-input multi-output scenarios [30,31]. We simultaneously consider population, capital stock, energy usage, and GDP to reexamine the emission convergence of the RCEP countries.

In the DEA model, we start by modelling production technologies. Assume that there are $j = 1, \dots, N$ decision-making units (DMUs). In this study, these DMUs are the 15 RCEP countries. Suppose that each DMU uses an input vector, $x \in R^I$, to jointly produce a desirable output vector, $y \in R^M$, and an undesirable output vector, $b \in R^S$. R is a nonnegative real space of finite dimension I, M , and S , respectively. The production technology $Tech$ is expressed as:

$$Tech = \{(x, y, b) : x \text{ can produce } (y, b)\}$$

$Tech$ satisfies the production theory axioms, where inactivity is always possible, and a finite amount of input can only produce a finite amount of output. Additionally, inputs and desirable outputs are freely disposable, whilst weak disposability is assumed for desirable outputs and undesirable outputs. Mathematically, the assumptions can thus be formulated as:

- (i) If $(x, y, b) \in Tech$ and $0 \leq \theta \leq 1$, then $(x, \theta y, \theta b) \in Tech$
- (ii) If $(x, y, b) \in Tech$ and $b = 0$, then $y = 0$

Considering N DMUs over T periods exhibiting constant return to scale, we can construct a global production possibility set using the DEA model [32] as follows:

$$Tech = \{(x, y, b) : \begin{aligned} &\sum_{t=1}^T \sum_{n=1}^N \lambda_n x_{in}^t \geq x_i, i = 1, \dots, I \\ &\sum_{t=1}^T \sum_{n=1}^N \lambda_n y_{mn}^t \geq y_m, m = 1, \dots, M \\ &\sum_{t=1}^T \sum_{n=1}^N \lambda_n b_{sn}^t \leq b_s, s = 1, \dots, S \\ &\lambda_n \geq 0; n = 1, \dots, N; t = 1, \dots, T \end{aligned}\} \quad (8)$$

where x, y , and b represent individual input, desirable output, and undesirable output, respectively; I, M , and S represent the number of inputs, desirable outputs, and undesirable outputs, respectively; λ_n is the non-negative intensity variable that suggests the weight of each DMU to construct the production frontier. The aforementioned expression indicates that no DMUs can exceed the best combination of the currently realized production practice and that any production technology that is less efficient than the production frontier is possible. Therefore, the data envelopment model considers constraints in all the production factors while measuring performance.

We can apply the directional distance function (DDF) to construct the target function to the DEA model. Specifically, the non-radial DDF (NDDF) is adopted in this study owing to its stronger discriminatory power and more accurate expression in the production expansion process compared with the radial DDF model [33,34]. The NDDF is expressed as follows:

$$\vec{D}(x, y, b; g) = \sup \{w^T \beta : (x, y, b) + g \cdot \text{diag}(\beta) \in Tech\} \quad (9)$$

where $\vec{D}(\cdot)$ is the DDF, w is the weight vector of inputs and outputs, g is the direction vector, and β is the scaling vector. We set the directional vector as $(-P, -K, -E, G, -C)$ for population (P), capital stock (K), energy use (E), GDP (G), and CO₂ emissions (C), respectively, and the weight vector as $(1/9, 1/9, 1/9, 1/3, 1/3)$. This follows the spirit of

green total productivity [35,36]. By integrating the DEA model, we established a global DDF model. The NDDF value of each DMU can be calculated using the following equation:

$$\begin{aligned} \vec{D}(x, y, b; g) = \max & \left(w_i \beta_i^{xt} + w_m \beta_m^{yt} + w_s \beta_s^{bt} \right) \\ \text{s.t. } & \sum_{t=1}^T \sum_{n=1}^N \lambda_n^t x_{in}^t \leq x_{in}^t - \beta_i^{xt} g_{xi}^t, \quad i = 1, \dots, I \\ & \sum_{t=1}^T \sum_{n=1}^N \lambda_n^t y_{mn}^t \geq y_{mn}^t + \beta_m^{yt} g_{ym}^t, \quad m = 1, \dots, M \\ & \sum_{t=1}^T \sum_{n=1}^N \lambda_n^t b_{sn}^t = b_{sn}^t - \beta_s^{bt} g_{sn}^t, \quad s = 1, \dots, S \\ & \beta_i^{xt}, \beta_m^{yt}, \beta_s^{bt} \geq 0; \lambda_n^t \geq 0; \quad t = 1, \dots, T; \quad n = 1, \dots, N \end{aligned} \quad (10)$$

Solving this equation gives the optimal values for scaling factors (β_p^* , β_K^* , β_E^* , β_G^* , β_C^*) for each DMU, which indicates the potential expansion or inefficiency of the DMU in each input/output while considering constraints in other input/output directions. For example, β_C^* indicates the inefficiency of a DMU (i.e., a country) in their CO₂ emission. The scaling factor β_C^* ranges from zero to one. The higher the scaling factor is, the lower its emission efficiency is. A scaling factor of zero means the country is efficient in its CO₂ emissions. Supposing that β_p^* and β_C^* are the optimal values for a DMU in population and CO₂ emissions, respectively, that is, the maximum expansion of a DMU in its corresponding population and CO₂ emissions owing to its inefficiency [34,37], we can define a series of emission performance indexes. We first introduce the carbon emission efficiency (CEE):

$$CEE = 1 - \beta_C^* \quad (11)$$

Here, β_C^* measures the reduction needed for a DMU in CO₂ emissions to reach its best performance as illustrated above. When examining the convergence, we can therefore test if the CEE of all the DMUs converges to a certain level, i.e., low-performance DMUs (low CEE) catch up with high-performance DMUs (high CEE). We further introduce the carbon–population performance (CPP), which is expressed as follows:

$$CPP = \frac{(1 - \beta_C^*) + (1 - \beta_p^*)}{2} = 1 - (\beta_C^* + \beta_p^*)/2 \quad (12)$$

The CPP measures the performance of a DMU in not only carbon emissions but also population utilization. The same weight is given to them while other factors are also constrained. If the CPP converges to a certain level, it indicates that poor-performing DMUs will catch up with the leaders in both carbon emissions and population utilization (effective employment level), that is, DMUs with a low CEE and low population utilization efficiency (PUE) can rapidly increase their performance in the two dimensions. A high CEE but low PUE DMU may catch up with PUE, and a high CEE and PUE will maintain its current status.

Following the spirit of the per capita emission approach, we also introduce the carbon–population ratio (CPR) as follows:

$$CPR = \frac{1 - \beta_C^*}{1 - \beta_p^*} \quad (13)$$

Unlike the pure efficiency-based measurements that evaluate a DMU's multi-dimensional performance versus the best-attainable performance [34], the CPR measures the ratio between the CEE and PUE, thereby examining whether there exists a balance between the CEE and PUE while considering other production factors, that is, whether carbon emission efficiency is correlated with population efficiency.

2.3. Data

The annual data of the studied countries from 2000 to 2017 are collected from a variety of resources: Population data are collected from the Population Division of the United Nations [38], CO₂ emissions data are collected from Our World in Data [39], capital stock and GDP data at a constant price are collected from the International Monetary Fund [40–42], energy consumption data are collected from the International Energy Agency [43], and export data are collected from the World Bank [44]. All data are publicly accessible. The compiled data can be accessed at https://github.com/panday1995/2021_RCEP_carbon_convergence, accessed on 22 January 2021, Table 1 shows the descriptive statistics of the collected data.

Table 1. Descriptive statistics of the data from 2000–2017.

Variables	Unit	Mean	St. Dev.	Minimum	Maximum
Population	10 ³ persons	143,071.83	330,902.45	333.17	1,421,021.79
Capital	10 ⁹ US dollars	4558.09	9297.97	13.83	64,687.64
Energy	10 ³ t oil-eq	159,549.39	376,253.62	551.00	2,005,821.00
GDP	10 ⁹ US dollars	714.38	1460.25	1.72	5623.04
CO ₂ emissions	10 ⁶ t CO ₂ -eq	706.17	1886.25	0.96	9838.75
Export	10 ⁹ US dollars	214.20	349.12	0.28	1809.34

3. Empirical Results

3.1. Per Capita Emission Convergence

Figure 1 presents the evolution of the per capita emissions of the RCEP countries. The per capita emissions of most RCEP countries have increased compared to their corresponding level in 2000. Economically developed countries, e.g., Australia, Japan, New Zealand, and Singapore, have slightly reduced their per capita emissions. The per capita emissions of Brunei and Singapore show wild fluctuations. Brunei's per capita emissions leapfrogged from 12.79 t in 2006 to 22.16 t in 2007 and have winded down in the following years. South Korea was the only developed economy that has exhibited a gradual increase in per capita emissions. The difference in per capita emissions between high-emission countries, such as New Zealand, South Korean, and Australia, and low-emission countries, such as Myanmar and Philippines, does not shrink. The plot shows no evidence that low per capita emission countries may catch up with high emissions countries.

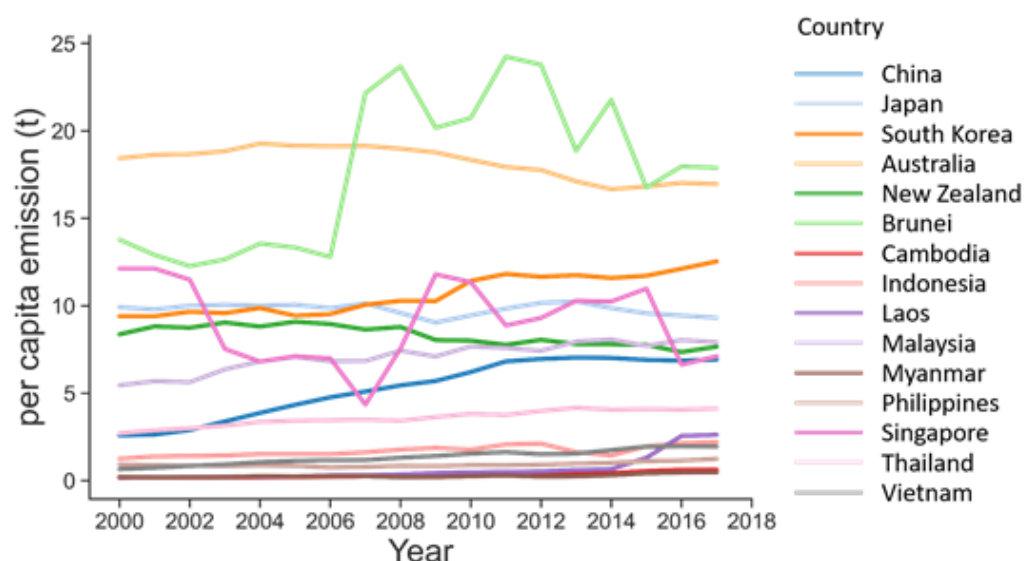


Figure 1. Evolution of the per capita CO₂ emission of the RCEP countries between 2000 and 2017.

We then test the convergence of per capita emissions of the RCEP countries, as shown in Column (1) of Table 2. The β coefficient is statistically significant with a negative sign. The β coefficient in our model indicates the effect of the past level of per capita emission on the growth rate of a country's current per capita emission. A negative β coefficient implies that per capita emissions of the examined countries will diverge—those low-emission countries will be persistently lower in per capita emissions than those high-emissions, and the emission gap will expand rather than shrink. In contrast, a positive β coefficient suggests a lower growth rate of per capita emissions for high-emission countries and a higher growth rate for low-emission countries. Eventually, the low per capita emission countries will catch up with high-emission countries after a certain period of time, and all the countries' per capita emissions will reach an equilibrium level.

Table 2. Test on the convergence of per capita emission in the RCEP countries.

	(1) RCEPs	(2) ASEANs	(3) Non-ASEANs	(4) East Asians
β	−0.0475 *** (0.001)	−0.0621 ** (0.026)	−0.0867 *** (0.001)	−0.1022 *** (0.001)
α	−0.0959 *** (0.002)	−0.0030 ** (0.043)	−0.2210 *** (0.000)	−0.3357 *** (0.000)
E_{eq}	NA	NA	NA	NA
C_T	NA	NA	NA	NA
First-stage F	17.38	8.28	31.85	34.55

Parentheses (·) denotes the p -values; RCEPs indicate the 15 RCEP countries; ASEANs indicate the 10 ASEAN countries; non-ASEANs represent the other 5 RCEP countries that do not participate in the ASEAN; East Asians denote China, South Korea, and Japan. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.10$.

Hence, the statistically significant negative β coefficient in our results indicates that the per capita emissions of the RCEP countries is diverging rather than converging. Specifically, with per capita emissions being 1% higher, a country's emission growth rate was 0.0486% higher (transformed from $-(1 - e^{-\beta})$). This is true despite the potential green technology diffusion effect, knowledge spillover effect, and the like [45]. The diverging per capita emissions in the RCEP countries is no surprise, as these countries have drastically different international specialization. Given the divergent pattern, a united carbon trading market that allocates emission quotas based on the per capita emission approach may make high-emission countries, such as South Korea, Australia, and Brunei, bear continuing welfare losses due to the outflow of emission allowances. Therefore, emission allocation mechanisms based on per capita emissions may not be appropriate for climate negotiations in these countries. The first-stage F -statistic of the model is 17.68, which is larger than 10, thereby supporting the validity of the instrumental variable in the model [23,24,46].

There may be group convergence in sub-regions of the RCEP trading bloc due to their similar economic structure or geographical proximity [47,48]. To test this, we decompose the RCEP countries into subgroups—ASEANs and non-ASEANs (See Notes of Table 2 for a detailed group division)—and tested their convergence in per capita emissions. Neither ASEAN nor non-ASEAN countries show a statistically significant converging trend, suggesting that no absolute per capita emissions convergence may occur in these sub-regions either. Moreover, the results show that the β coefficient for any subgroups (−0.0621, −0.0867, and −0.1022 for ASEANs, Non-ASEANs, and East Asians, respectively) is larger in absolute value than the RCEP countries as whole. Of note, the F statistic in ASEAN countries does not exceed 10, which suggests that the instrumental variable may not be sufficiently correlated with the endogenous variable. Nonetheless, to keep the consistency of instrumental variable selection, we retain the results. Despite that, the existing results show that per capita emissions diverge faster in those sub-groups. This is possibly because of the highly specialized regional supply chain division in these subgroups. For examples, China has long been a factory for South Korea and Japan. Here, the divergence force (international specialization) outweighs the convergence force

(knowledge diffusion). Therefore, initiating emission trading in those subgroups will also cause a severe emission trade imbalance if the per capita emission approach is used for emission quota allocations. Alternative approaches are needed to build the foundation of cooperative emission mitigation in the RCEP countries.

3.2. Per Capita Emission Convergence

3.2.1. Emission Performance of the RCEP Countries

In light of the limitations of the per capita emissions approach, we develop emission performance indices that consider not only the population but also the energy usage, capital stock, and economic output, such that a different perspective on the convergence of the RCEP countries is obtained.

Figure 2 presents the emission performance of the 15 RCEP countries between 2000 and 2017. Detailed results are provided in the Supplementary Materials. The average *CEE*, *CPP*, and *CPR* values were 0.6242, 0.5082, and 8.3925, respectively.

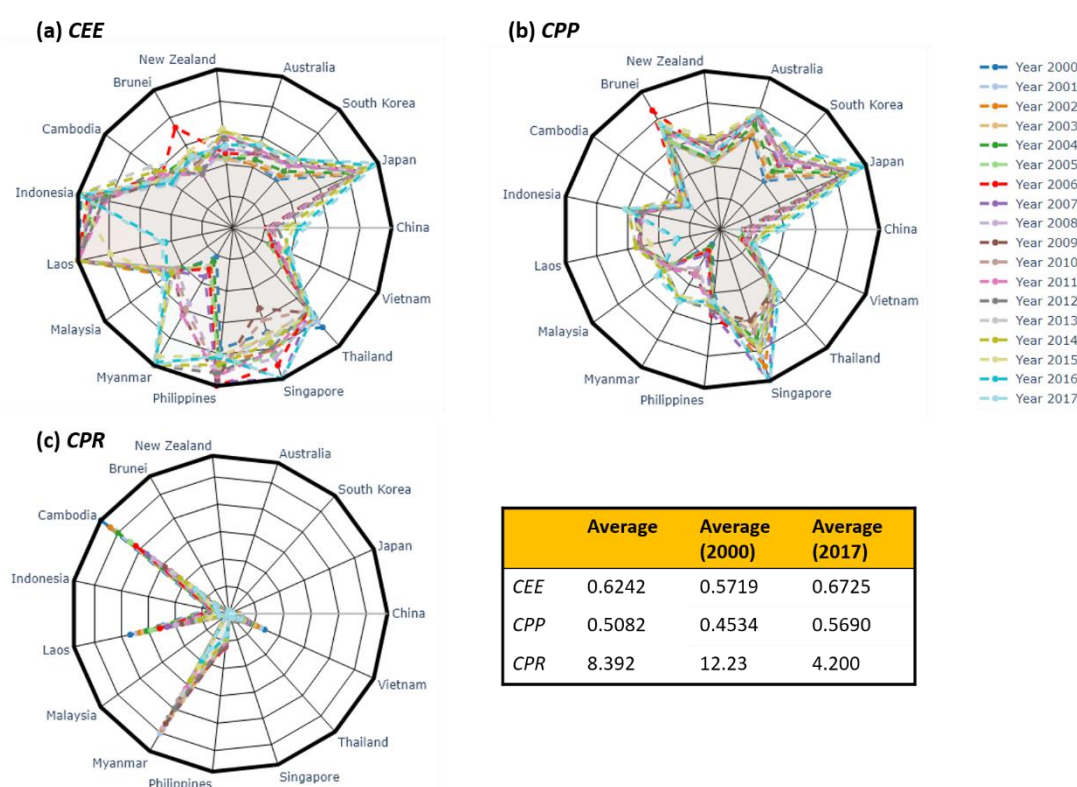


Figure 2. Emission performance of the 15 RCEP countries from 2000–2017. (a) Carbon emission efficiency (*CEE*); (b) Carbon-population performance (*CPP*); (c) Carbon-population ratio (*CPR*). For *CEE* and *CPP*, the maximum value (the outmost layer of the radar chart) is 1 and the minimum is 0; for *CPR*, the maximum and minimum are 60 and 0, respectively. Detailed numerical results are in Table S1, Supplementary Materials.

An average *CEE* of 0.6242 indicates that under the current environmental technology mix, the RCEP countries can achieve a maximum *CEE* increase of 37.6%, that is, they can reduce their carbon emissions as a whole by 37.6%. The average *CEE* increases yearly from 0.5719 in 2000 to 0.6725 in 2017, while the standard error decreases from 0.0675 in 2000 to 0.0594 in 2017, suggesting that the *CEE* of the RCEP countries may converge to the best performing value. Laos showed a high *CEE* before 2015, which dropped rapidly in the subsequent years due to its fast-growing CO₂ emissions. Japan had the highest *CEE* throughout the study period, while China and Vietnam displayed poor *CEE* performances, although with evidence of an increase. Developed countries, such as Australia, South Korea, and New Zealand, did not exhibit apparent advantages over developing countries;

however, the results show that their *CEE* performances exhibited gradual increments over time.

The average *CPP* had an even larger uptake from 0.4534 in 2000 to 0.5690 in 2017, whereas its standard error also increased from 0.0584 to 0.0617. An average *CPP* of 0.5082 suggests that the RCEP countries had a larger potential to increase their *CPP* compared their *CEE*. Japan and Singapore remained the two leading countries in *CPP*, and their performance has been constantly improving. Laos was no longer the best-performing country in terms of *CPP*, suggesting it has a poor performance in terms of the mobilizing population factor, although its *CEE* is high. The *CPP*s of Indonesia, Cambodia, Myanmar, and the Philippines were all significantly lower than their counterparts' *CEEs*, indicating that they all had a less effective population management in their economies. Correspondingly, Figure 2c indicates that the *CPR*s of Laos, Cambodia, and Myanmar were much higher than those of the others, thus implying that they had a high efficiency in emission management, but a low efficiency in the mobilizing population factor. Furthermore, the *CPR*s of Myanmar, Vietnam, and Cambodia have been continuously decreasing, while the *CPR*s of Laos and Vietnam continued to increase despite its high *CPR* (detailed results are shown in Table S1 of the Supplementary Materials)—suggesting a potential *CPR* diverging trend of the RCEP countries.

3.2.2. Converging Emission Performance in the RCEP Countries

Columns (1), (3), and (5) of Table 3 show the test results of the absolute convergence of emission performance in the RCEP countries. The *CEE* and *CPP* will converge in the RCEP countries, while, on the contrary, the *CPR* will diverge in the future. The convergence of the RCEP countries in the *CEE* and *CPP* implies that underdeveloped countries are on a trajectory to catch up with the developed countries in this region. For *CEE* being 1% higher, its *CEE* growth rate was 0.0783% lower. While 1% higher in *CPP* indicates 0.0452% lower in *CPP* growth rate. The *F*-statistic demonstrates the validity of the instrumental variables used in the test. The β -convergence test shows that the *CEE* and *CPP* will converge at 0.8187 and 0.7831 with time spans as short as 3.1996 and 3.7659 years, respectively. The results indicate *CEE* and *CPP* are converging at a fast pace. The fast-converging speed may imply that converging forces are already taking a role before the signing of the RCEP agreement. A socioeconomic ground for a unified carbon market is taking its shape in RCEP countries. Cooperative carbon emission mitigation can be an immediate option for RCEP countries.

Table 3. Test on the convergence of emission performance in the RCEP countries.

Region Index	<i>CEE</i>		RCEPs <i>CPP</i>		<i>CPR</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
β	0.0816 ** (0.023)	0.0857 ** (0.021)	0.0463 ** (0.013)	0.0568 ** (0.012)	−0.0437 *** (0.001)	−0.0417 *** (0.001)
$Ln(EX)$		0.0171 (0.788)		0.0225 (0.638)		0.0242 (0.713)
α	−0.0156 (0.129)	−0.0032 (0.963)	−0.0110 (0.238)	−0.0818 (0.178)	−0.0103 (0.193)	−0.0763 (0.178)
E_{eq}	0.8187	0.9611	0.7831	0.2269	NA	NA
C_T	3.1996	3.1606	3.7659	3.5621	NA	NA
First-stage F	11.37	11.88	12.02	12.5492	19.33	20.02

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We further examine the impact of trade on the convergence of emission performance in the RCEP countries, as shown in Columns (2), (4), and (6) of Table 3. Though the impact of *EX* on *CEE*, *CPP*, and *CPR* has no statistical significance, the positive coefficients of $ln(EX)$ suggest that the growth of *CEE*, *CPP*, and *CPR* was accompanied by an increase in

EX. 1% higher in *CEE* indicated 0.0821% lower in the growth rate of *CEE*. Similarly, 1% increase in *CPP* can lead to 0.0552% decrease in the growth rate of *CPP*. By conditioning on the *EX*, the convergence speed of the RCEP countries increases. The time required to reach equilibrium level decreased from 3.1996 to 3.1606 years for the *CEE* and from 3.7659 to 3.5621 years for the *CPP*. *CPR* is diverging, suggesting there is no balance between the evolution of *CEE* and *PUE*.

4. Discussion

Although several Asian countries have pledged their carbon-neutrality targets in 2020 [49], the traditional “pledge and review” climate agreement that implicitly constrains emission reduction activities inside a country’s territory may be insufficient to combat climate change [50]. The pressing matter of climate change calls for effective multilateral climatic cooperation to create synergies across borders for a rapid emission reduction. We herein studied the feasibility of cooperative emission mitigation in the RCEP countries through convergence analysis. We adopt a dynamic β -convergence model to investigate the emission convergence of the RCEP countries and compare emission convergence from different perspectives. Though the β -convergence model has been widely employed to study regional emission convergence, seldom have papers provided convergence analysis other than per capita emissions [10]. Some have adopted the framework to analyse emission efficiency convergence in Australia [51] or China [16,52]. Here, we provide new evidence of emission convergence for the RCEP countries.

None of the tested country groups show evidence of β -convergence from a per capita emissions perspective. This finding aligns with other literature [10,53], where evidence of convergence only emerges in the OECD countries or at a state level inside a country’s territory—those that have similar economic structure and substantial multilateral trade volume. There may exist a persistent emission gap between the high per capita emissions countries and the low per capita emissions countries. This is ascribed to that the traditional “per capita emission” approach to examine the emission convergence ignores important structural characteristics of an economy [10]. For instance, its underlying egalitarianism value neglects other principles, such as natural resource endowment and economic or environmental efficiency, which is implicitly unfair to efficient emitters. Thus, more scholars have been taking a more inclusive view on carbon emission when considering emission quota allocations or cross-border emission trading [15,54].

Several scholars have proposed emission allocation schemes based on these composite indicators [55,56]. However, an empirical ground for these emission allocation schemes is lacking. Therefore, we construct composite emission performance indicators that consider an array of important socioeconomic factors, including capital stock, energy use, population, and economic outputs (GDP). These composite indicators are based on different principles, i.e., a fairness-based principle or an efficiency-based principle. We examine the convergence of the RCEP countries on these emission performance indicators and find that *CEE* and *CPP* show absolute convergence, although *CPR* shows a diverging pattern. The findings imply that these indicators, especially *CEE* and *CPP*, are applicable in regional climate policy cooperation. For example, emission budget allocation can be based on countries’ *CEEs* and *CPPs* [55]. Adapting these indicators can lead to less cross-border resources and capital transfer in market mechanisms compared to the per capita emissions approach. Therefore, evidence of the convergence of the *CEE* and *CPP* opens up a new opportunity for developing an integrated CO₂ emission allocation and trading scheme in the Asian-Pacific region.

Finally, by examining the influence of export on the convergence of the *CEE* and *CPP*, we find that even though the *EX* has no statistically significant influence on the convergence of the *CEE* and *CPP*, it accelerates their convergence. Thus, the finding suggests that the establishment of the RCEP free trade agreement will further promote the convergence of the *CEE* and *CPP*. Therefore, the establishment of the RCEP trading bloc can further

enhance the legitimate development of an integrated emission allocation scheme and trading market in the RCEP countries.

5. Conclusive Remarks and Policy Implications

This paper contributes to the literature in the following ways:

- (1) With the establishment of the RCEP free trade agreement, this paper is the first to investigate the feasibility of cooperative CO₂ mitigation in the participating countries.
- (2) To this end, a dynamic β -convergence approach with instrumental variables is adopted based on the previous cross-sectional β -convergence. This enables the investigation of the converging process in a panel data setting.
- (3) We adopt the DEA model and construct an array of emission performance indicators that consider multiple production factors and reconfirm the convergence of the RCEP countries in connection to these performance indicators.

The empirical results show that although the convergence hypothesis does not hold for the per capita emissions, the emission performance indices constructed using the DEA model converge because they consider a set of emission-driving forces. This empirical evidence suggests that although some countries outperformed others at the current state, this performance difference will eventually disappear following the converging process. Thereby, we propose that if a unified emission trading framework is implemented in the RCEP region and an appropriate emission budget allocation principle is adopted, no country will acquire substantial and persistent carbon rent from others. Trading can accelerate regional emission performance convergence. Thereby, the RCEP free trade agreement may benefit the region's emission performance convergence as it frees regional trade. Thus, climate-ambitious countries in the RCEP agreement should proactively embrace trade openness, leveraging the free trade agreement to not only boost their economies, but also realize cooperative CO₂ emission mitigation.

The current work is still subject to some limitations: first, owing to data scarcity, we use the total *EX* as a proxy for regional trade in the RCEP, which may lead to a bias in estimating the effect of trade on convergence. It may also bias due to trade-flow-based spatial dependence. Accurate trade data for the RCEP countries are needed to remedy this issue. To this end, regional climate cooperation must take environmental and economic data openness as an integral part. In addition, developing countries may lack the in-need financial resources to deploy the relevant data measurement and reporting infrastructure [57]. Mechanisms to aid data infrastructure in developing countries should be investigated in future work. Second, climate and natural resource endowment are other characteristics that must be considered when conceptualizing emission reductions, but these are neglected owing to data scarcity. Future works may consider these factors with ecological value assessment frameworks. Third, there are other structural features, such as innovations spillovers, regionally heterogeneous emission mitigation policies, among others, which may affect emission convergence but is lacking in discussions about regional climate cooperation [58]. Their roles need further investigation with a more comprehensive dataset. Finally, we built DEA-based composite indicators on the top of green total-productivity models, considering only *CEE* and *CPP*. More efficiency and productivity indicators may be used for robustness checks.

Supplementary Materials: The following are available online at <https://www.mdpi.com/article/10.3390/su131810135/s1>, Table S1: Detailed emission performance of the fifteen RCEP countries from 2000–2017.

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