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Per capita carbon emissions convergence in developing Asia: A century of evidence from covariate unit root test with endogenous structural breaks

Takashi Matsuki [a,*], Lei Pan [b]

[a] Faculty of Economics, Osaka Gakuin University, 2-36-1 Kishibeminami, Suita-City, Osaka, Japan
[b] School of Accounting, Economics and Finance, Curtin University, Kent St, Bentley, WA 6102, Australia

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ABSTRACT

Many studies address the convergence in per capita CO2 emissions. However, whether countries with lower initial per capita emission levels can "catch up" with more emission-intensive countries is unknown. Utilising historical CO2 emission data from 1907, this study investigates whether the per capita CO2 emissions of seven developing Asian economies; namely, China, Indonesia, India, Myanmar, the Philippines, Taiwan, and Thailand, catch up with or converge toward that of the US in the long run. We simultaneously examine the existence of per capita CO2 emissions convergence and the statistical contribution of the emissions drivers using the most recently developed covariate augmented Dickey-Fuller test, which allows for endogenous structural breaks. The main results show firm evidence of catching-up or relative/absolute convergence between the Asian economies and the US in terms of per capita CO2 emissions. Emissions drivers such as population and real GDP per capita growth may encourage the Asian economies to achieve and to maintain the long-run convergence toward the reference country.

1. Introduction

The interrelationship between economic activities and the environment has led to significant discussions among researchers and politicians.[1] The latest research focuses on the impacts of climate change and air pollution on different aspects of the real economy such as agriculture (Cui, 2020; DePaula, 2020; Malikov et al., 2020), labour markets (Aragon et al., 2017; Huang et al., 2020) and migration (Vinent et al., 2019; Oliveira and Pereda, 2020). On the policy front, while the Kyoto Protocol, which aims to prevent global warming, expired in 2012, a range of new policy measures were designed to restrict greenhouse gas emissions. However, one important issue with the implemented policies is the feasibility of per capita emissions allocation schemes. This issue has led to a long-term policy debate on the trade-off between equity and efficiency distribution. In particular, the principle of equal per capita emissions is appealing to many on grounds of fairness. The idea is that each individual has an equal right for absorbing greenhouse gas emissions regardless of past actions and future opportunities. Following the rule, this may involve setting a long-term emissions budget and sharing this budget among countries to equalise per capita emissions in the long run (so called absolute convergence). Alternatively, considering country heterogeneity, per capita emissions can be forced to converge within a pre-defined period, but to different steady-states (so called conditional convergence). In contrast, if emissions do not converge, then we could see substantial international transfers of rents through carbon allowance trading or relocations of emission-intensive industries. Efforts to elicit participation in a global climate commitment may not garner support from developed countries. For example, the US strongly opposed the international climate negotiations. Countries such as the US argue that the per capita emissions principle ignores country-specific characteristics such as natural resource endowments, and hence prefer an allocation scheme that maximises the value of resources (i.e., the efficiency principle).

Understanding the dynamics of per capita CO2 emissions has fuelled a burgeoning literature on region- or country-level convergence. We can group the empirical research on per capita CO2 emissions convergence based on the use of three different convergence measures: beta (β), sigma (σ) and stochastic convergence. Beta convergence follows the neoclassical economic growth literature (e.g., Solow, 1956) and focuses on testing the downward linear trend between the initial level of pollution and the growth rates of per capita emissions across countries. Several studies examined the beta convergence of CO2 emissions (Strazicich and List, 2003; Brock and Taylor, 2010). A negative sign on the coefficient

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* Corresponding author.
E-mail addresses: matsuki@ogu.ac.jp (T. Matsuki), lei.pan@curtin.edu.au (L. Pan).

[1] CADF test: covariate augmented Dickey-Fuller test (hereafter, CADF test).
GLSu: Dickey-Fuller/Generalized Least Squares *U* test (Elliott, 1999) (hereafter, GLSu test)
IEA: International Energy Agency (IEA).

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of the initial level of per capita emissions indicates evidence of convergence across countries. Beta convergence is a necessary, but not sufficient, condition for sigma convergence. Sigma convergence considers the intra-distributional behaviour and dynamics of the per capita growth of a cross-section of countries. The original idea of sigma convergence described in Barro and Sala-i-Martin (1992) would translate into a decrease in the cross-sectional variance of per capita emissions over time (Panopoulou and Pantelidis, 2009; Camarero et al., 2013). The final approach, stochastic convergence, indicates that shocks to per capita emissions for one country relative to another (or mean value of the sample) are temporary. It aims to investigate the time series properties of per capita emissions and thus uses various types of unit root tests (Westerlund and Basher, 2008; Yavuz and Yilanci, 2013). The absence of unit roots implies CO2 emissions convergence.

Overall, the empirical evidence gathered so far on per capita CO2 emissions convergence across different countries remains broadly inconclusive. On the one hand, some studies examined how the cross-sectional distribution of relative per capita emissions provides evidence of divergence worldwide but convergence between large polluters (Stegman, 2005; Aldy, 2006). On the other hand, studies employing time series techniques reported ambiguous findings, with divergence between OECD countries in some studies (Barassi et al., 2008) but convergence within groups of more heterogeneous countries (Westerlund and Basher, 2008; Panopoulou and Pantelidis, 2009). However, the pollution convergence literature has neglected the catch-up hypothesis.

The contribution of this paper to the literature is three-fold. First, this study is one of the few that uses long historical data for multiple countries to investigate convergence in per capita CO2 emissions. The long sample period enables us to exploit the large historical variations in the data than, say, post-World War II data in which most variables have been trending upward over time. Although a small number of studies examined convergence in CO2 emissions using historical data, they focused either on developed countries only (see e.g., Herrerias, 2012; Frohlich and Blossom, 2019), a collection of both developing and developed countries (see e.g., Westerlund and Basher, 2008; Christidou et al., 2013; Awaworyi Churchill et al., 2018) or testing convergence using data for a single time series only (see e.g., Awaworyi Churchill et al., 2020a; Awaworyi Churchill et al., 2020b). The present study differs from these studies in that it considers emerging economies alone and utilises the information on covariates to investigate the convergence of carbon emissions. Second, to the best of our knowledge, this is the first attempt to provide evidence of converging trends in the sense that countries with lower initial per capita emission levels are experiencing higher emissions growth and hence “catching up” with the more emissions-intense countries. We examine this issue by looking at countries in developing Asia. Asian countries play a major role in global CO2 emissions. China and India are among the top ten emitters worldwide, and their contribution has been rising over time. Studying Asian economies in this respect is therefore very important. However, no studies so far have focused on developing Asia exclusively. The only study related to our work is that by Awaworyi Churchill et al. (2020a), who examined the catching-up effect by looking at whether the relative per capita CO2 emissions for their sample countries deviated, relative to the mean, from their long-term emissions path. Our study differs in terms of the catching-up effect measures. We use deviations from a reference country (the US) to test whether the catching-up hypothesis holds in Asian countries over the long term. Third, we use a more effective approach by employing additional information to consider the convergence issue in Asia. While some previous studies find convergence, its signal is too weak to be detected by ordinary testing methods that use a single time series. The signal would strengthen if we could overcome the problem of the lack of information for the test. We therefore interpret the existence of convergence. Specifically, we test if the use of additional information makes convergence hold, and if so, then per capita CO2 emissions convergence still exists. To do so, we adopt the most recently developed covariate augmented Dickey-Fuller test with multiple structural breaks, proposed by Matsuki (2019). This method allows us to simultaneously confirm the existence of convergence and the statistical contribution of emission drivers.

Foreshadowing the main results, we find that since the regional CO2 emissions disparity narrows as country continues to grow, the per capita CO2 emissions in Asian countries will catch up with the US in the future.

The remainder of the paper is structured as follows. Section 2 describes the data set. Section 3 presents our empirical methodology. Section 4 reports and discusses the empirical results. Section 5 concludes.

2. Data

We use annual data over the period 1907–2011 for China, Indonesia, India, Myanmar, the Philippines, Taiwan and Thailand. Due to limited data availability, the sample for Myanmar and Thailand starts from 1928 and 1931, respectively. The data on total carbon dioxide emissions are in thousands of metric tons and sourced from the Carbon Dioxide Information and Analysis Center (CDIAC). We obtained the data on population size from the Maddison Project database. To obtain per capita CO2 emissions, we simply divided total CO2 emissions by population size. Fig. 1 plots the trends in per capita CO2 emissions for each country. The per capita CO2 emissions series in Taiwan is much higher than those of the other Asian countries since the 1960s. In fact, Taiwan is in the highest 25 countries for per capita CO2 emissions worldwide.[2] Moreover, Fig. 1 shows that China's per capita CO2 emissions have grown sharply since China's first adopted its reform and opening-up policy toward the end of the 1970s. Fig. 2 plots the difference in logs of per capita CO2 emissions between seven Asian economies and the US. Although some series, particularly those for the Philippines, Myanmar, and Thailand, have spikes at specific dates, we can see a clear downward trend in all series over time. Does this result mean that CO2 emissions levels in developing Asia caught up with those in high-income economies such as the US? Sections 3 and 4 provide empirical answers to this question.[3]

3. Empirical framework

The theoretical foundation of the catch-up hypothesis can be traced to the neoclassical Solow-Swan model. Following Solow (1956) and Barro et al. (1991), per capita real income growth rates are inversely related to the initial income levels corresponding to the early stages of development. This implies that the emissions of countries in developing Asia, which had lower initial levels of CO2 emissions per capita, will grow faster than the ones from a rich country such as the US. There is therefore a catching-up effect with the more polluting countries.

We examine whether the log of per capita CO2 emissions for each country is catching up with log of the steady-state value of per capita CO2 emissions or has already converged to it and is staying at a steady state. To this end, we adopt Bernard and Durlauf's (1996) and Hobijn and Franses's (2000) catching-up and convergence concepts. These concepts are often used to confirm long-run economic growth patterns in growth empirics. We utilise these for our analysis to reveal the long-run per capita CO2 emissions behaviours between developing Asian countries and the US.

Bernard and Durlauf (1996) state that the convergence of time series (e.g., per capita outputs) between two countries holds if the long-run

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[2] See Frohlich and Blossom (2019). These countries produce the most CO2 emissions. Available online: https://www.usatoday.com/story/money/2019/07/14/china-us-countries-thatproduce-the-most-co-2-emissions/39548763/. Wall Street.

[3] We consider three types of CO2 convergence patterns (absolute convergence, relative convergence and catch-up process) toward the US. Section 3 provides the definition of each pattern. In Figure 2, however, the first pattern (absolute convergence) is not clear, which means that the difference in per capita CO2 emissions between two countries does not completely disappear. Therefore, even when we obtain one test result that supports the existence of absolute convergence, we should be cautious until we find more supporting evidence. In Section 4, we discuss our test results based on this concept.

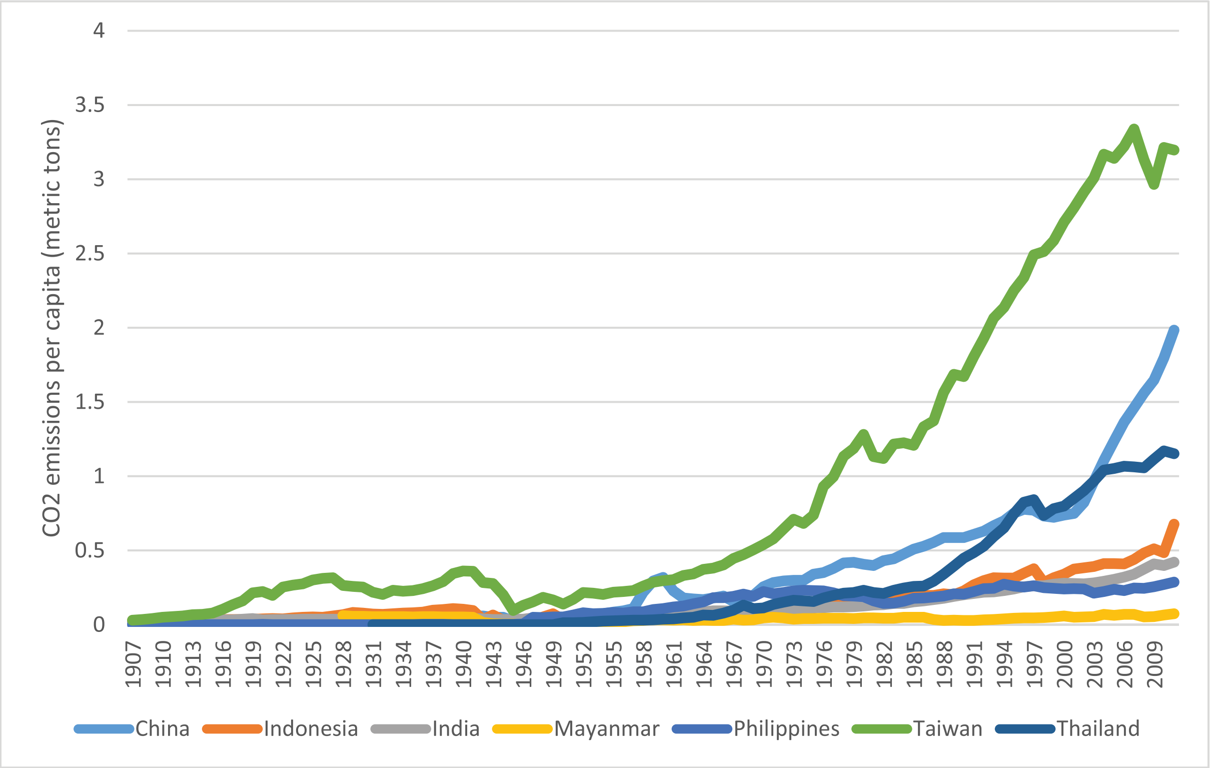

Fig. 1. CO2 emissions per capita in seven developing Asian countries (1907–2011).

forecasts of their differences approach zero as the forecasting horizon approaches infinity.

$$\lim_{h\to\infty} E\left(y_{i,t+h} - y_{j,t+h} | I_t\right) = 0 \tag{1}$$

where y_i and y_j are the time series of countries i and j, respectively; h is the forecasting horizon and I_t is an information set at fixed time t. This definition will be satisfied in the time series context if $y_{i,t+h} - y_{j,t+h}$ is a mean zero stationary process. That is, even if a certain shock affects the time series of two countries and their difference deviates from zero, this deviation is simply temporal, and the difference will revert to zero eventually. As Evans and Karras (1996) and Hobijn and Franses (2000) state, the zero-mean stationarity of the difference in time series is considered asymptotically absolute (or perfect) convergence (hereafter, absolute convergence).

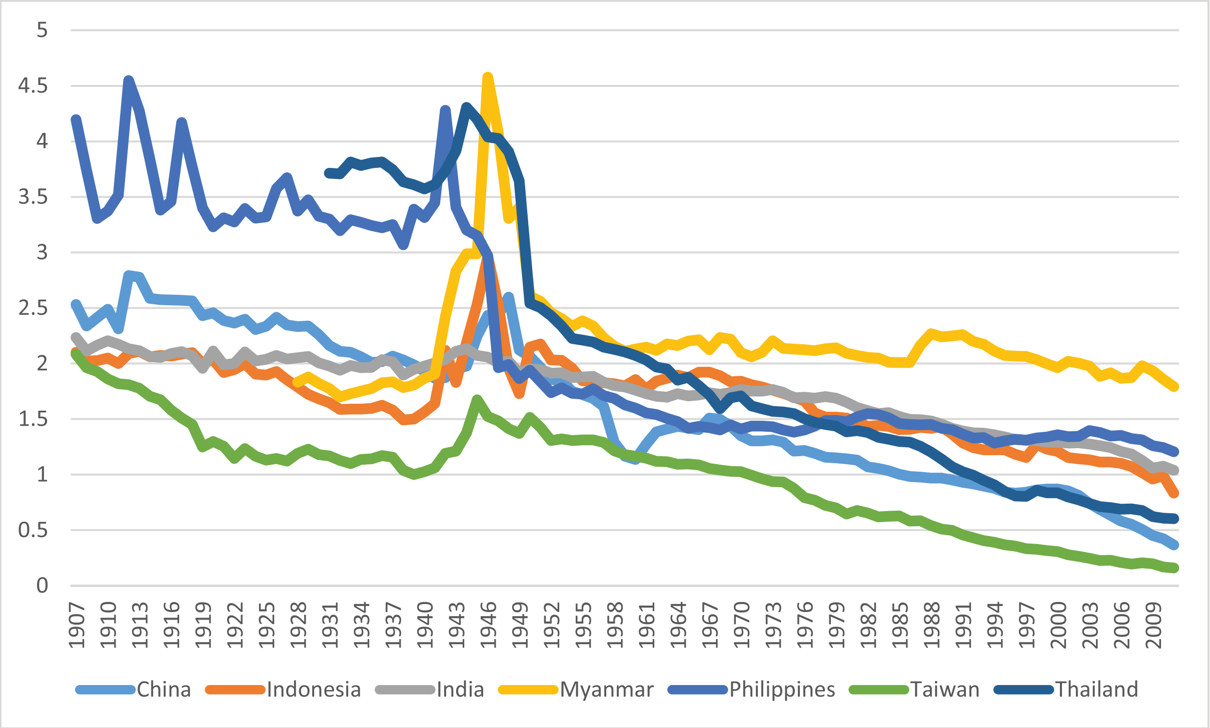

Fig. 2. Log of differences of per capita CO2 emissions (1907–2011).

On the other hand, when the difference shows the nonzero mean stationarity, it never vanishes, even in the long run, but does not divert and stably moves around its mean. In this case, the follower country is gradually catching up with the leader country but the gap in their time series is not perfectly removed even in the long-run steady-state in the sense of economic growth theory. This relation can be regarded as asymptotically relative convergence (hereafter, relative convergence).

As a catching-up concept, we also follow Bernard and Durlauf's (1996) definition:

$$E\left(y_{i,t+T} - y_{j,t+T} | I_t\right) < y_{i,t} - y_{j,t} \tag{2}$$

where $y_{i,t} > y_{j,t}$. Hence, countries i and j converge in terms of catching-up between t and $t+T$ if the difference in the two time series at t is expected to decrease in value at $t+T$. Based on this concept, we try to ascertain whether we observe a decreasing gap between two per capita CO2 emissions series in our model below.

The current and lagged difference time series are commonly used in empirical frameworks. In multi-country settings, deviations from a reference country are often taken as the convergence measure. In this study, we use the US as a reference country. Our baseline model is the augmented Dickey-Fuller type equation.

$$\Delta\widetilde{y}_t = \widehat{\boldsymbol{\alpha}}\boldsymbol{d_t} + \widehat{\delta}\widetilde{y}_{t-1} + \sum_{p=1}^{\overline{p}} \widehat{a}_p \Delta\widetilde{y}_{t-p} + error \tag{3}$$

where $\widetilde{y}_t = y_{i,t} - y_{j,t}$ and $\boldsymbol{d_t}$ is a deterministic vector, wherein $\boldsymbol{d_t} = \{\varnothing\}$, $\{1\}$ and $\{1, t\}$. When we confirm the existence of absolute and relative convergence, respectively, Eq. (3) includes $\boldsymbol{d_t} = \{\varnothing\}$ and $\{1\}$. When we confirm the existence of a catching-up process, it includes $\boldsymbol{d_t} = \{1, t\}$. We take the US as $y_{i,t}$ to avoid negative values of $y_{i,t} - y_{j,t}$ for conciseness.[4] In this case, if a catching-up process exists between countries, then the estimated coefficient of a time trend in $\boldsymbol{d_t}$ should take a negative value (Oxley and Greasley, 1995).

More importantly, we note that our long historical data may contain some structural changes. Therefore, we allow for this possibility of shifts in the time series in the hypothesis test. Moreover, we adopt more powerful tests, specifically the covariate augmented Dickey-Fuller test with/without structural breaks (CADF test) (Hansen, 1995; Matsuki, 2019). These tests consider endogenous structural breaks up to two into the alternative model and regression equation. The models for the case of two structural breaks are

$$\widetilde{y}_t = \boldsymbol{\theta d_t} + S_t \tag{4}$$

$$a(L)\Delta S_t = \delta S_{t-1} + \gamma DU(\tau_1)_t + \zeta DU(\tau_2)_t + v_t \tag{5}$$

$$v_t = b(L)'(\boldsymbol{\Delta x_t} - \boldsymbol{\mu_x}) + e_t \tag{6}$$

where $a(L) = 1 - a_1 L - a_2 L^2 - \ldots - a_p L^p$ is a p-th order polynomial in the lag operator; v_t is a white noise process, which covariates with $\boldsymbol{\Delta x_t}$ shown in Eq. (6); $\boldsymbol{\Delta x_t}$ is an m-vector; $\boldsymbol{\mu_x} = E(\boldsymbol{\Delta x_t})$ and $b(L) = b_{q2}L^{-q2} + \ldots + b_{q1}L^{q1}$ is a lag polynomial allowing for both q2 leads and q1 lags of $\boldsymbol{\Delta x_t}$ in Eq. (6). $DU(\tau_i)_t = 1$ for $t \geq \tau_i T$ and zero otherwise ($i = 1,2$); τ_i is the fraction of the i-break in $0 < \tau_i < 1$ and $\tau_i T$ is the i-break date ($i = 1,2$). In addition, the long-run covariance matrix is

$$\Omega = \sum_{k=-\infty}^{\infty} E\left[\begin{pmatrix} v_t \\ e_t \end{pmatrix} \begin{pmatrix} v_{t-k} e_{t-k} \end{pmatrix}\right] = \begin{pmatrix} \sigma_v^2 & \sigma_{ve} \\ \sigma_{ve} & \sigma_e^2 \end{pmatrix} \tag{7}$$

and the long-run squared correlation between v_t and e_t is

$$\rho^2 = \frac{\sigma_{ve}^2}{\sigma_v^2 \sigma_e^2} \tag{8}$$

ρ^2 shows the relative contribution of $\boldsymbol{\Delta x_t}$ to v_t at zero frequency. When $\boldsymbol{\Delta x_t}$ explains nearly all the zero-frequency movement in v_t, meaning $\sigma_{ve}^2 = 0, \rho^2$ takes zero. When $b(L) = 0, v_t = e_t$ and $\rho^2 = 1$, by substituting Eqs. (4) and (6) into (5), we obtain the following regression equation.

$$\begin{aligned}\Delta\widetilde{y}_t = {} & \widehat{\boldsymbol{\alpha}}\boldsymbol{d_t} + \widehat{\delta}\widetilde{y}_{t-1} + \widehat{b}(L)'(\boldsymbol{\Delta x_t} - \boldsymbol{\mu_x}) + \widehat{\gamma}DU(\tau_1)_t + \widehat{\zeta}DU(\tau_2)_t \\ & + \sum_{p=1}^{\overline{p}} \widehat{\alpha}_p \Delta\widehat{y}_{t-p} + error\end{aligned} \tag{10}$$

The break dates are endogenously determined to be located where the one-sided $t\left(\widehat{\delta}\right)$ is minimised in the sequential estimation over all possible combinations of break dates within $0 < \tau_1 < \tau_2 < 1$. More specifically, we conduct a grid search in the range of $0.1T < \tau_1 T < \tau_1 T + 1 < \tau_1 T + 2 < \tau_2 T < 0.9T$ to avoid detecting a single big structural break that exceeds one year multiple times during the estimation, where $\tau_1 T$ and $\tau_2 T$ are the first and second break dates, respectively. In other words, there is at least a two-year interval between the first and second break dates.

In this model setting, when there is no break ($\widehat{\gamma} = \widehat{\zeta} = 0$), Hansen (1995) derived the limiting distribution of t-statistic $t\left(\widehat{\delta}\right) = \widehat{\delta}/s\left(\widehat{\delta}\right)$ under the unit root null hypothesis ($\delta = 0$), which is a weighted sum of a Dickey-Fuller distribution and a standard normal one in the case of $\boldsymbol{d_t} = \{\varnothing\}$. Matsuki (2019) also extended this CADF test to consider endogenous structural breaks up to two and computed its critical values for $\boldsymbol{d_t} = \{\varnothing\}$ and $\{1\}$. We provide the critical values for $\boldsymbol{d_t} = \{1, t\}$, which are obtained in the Monte Carlo simulation and are tabulated in Table A1.[5]

4. Results and discussion

4.1. Preliminary results

To confirm the converging trends of the seven Asian countries' CO2 emissions toward that of the US, as a preliminary investigation, we first apply the augmented Dickey-Fuller test, the Dickey-Fuller GLSu test (Elliott, 1999) and the Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992) (hereafter, the ADF test, DF-GLSu test and KPSS test, respectively).[6] As Table 1a reports, the ADF test shows four and one significant rejections of the unit root null hypothesis for the regression model without a constant term and time trend (w/o constant & trend) and with a constant term and time trend (w/constant & trend), respectively. In addition, Table 1b shows that the DF-GLSu test suggests one rejection of the null for the case w/constant & trend. In contrast, the KPSS test results in Tables 1c and 1d provide strong significant rejections of the stationarity null hypothesis in most cases, which implies conflicting test results. One possible reason for this result is that neglecting the existing structural breaks in the CO2 emission series may lead to over-rejections of either the unit root or stationary null hypothesis (Perron, 1989; Leybourne et al., 1998; Montañés and Reyes, 1998), which is apparently observed in Fig. 2.

4.2. Benchmark results

Considering the potential structural breaks at unknown dates, we employ the tests proposed by Zivot and Andrews (1992) and

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[4] Of course, when we take the US CO2 emissions series as $y_{j,t}$ and use $\widetilde{y}_t = y_{i,t} - y_{j,t}$ in the subsequent model estimation and hypothesis test, the same results are obtained.

[5] The limiting distribution of the test for $\boldsymbol{d_t} = \{1, t\}$ is obtained by replacing a standard Wiener process in Eq. (11) of Matsuki's (2019) paper with a detrended standard Wiener process as $W^{\tau} \equiv W(r) - 2\int_0^1 (2 - 3s)W(s)ds - (6\int_0^1 (2s - 1)W(s)ds)r$.

[6] The optimum lag length for the regression equation is selected by the modified Akaike Information criterion (MAIC) suggested by Ng and Perron (2001). The maximum lag length is set at $12\left(\frac{T}{1000}\right)^{1/4}$. The subsequent tests conducted in this section also follow this procedure.

Table 1a
ADF test results.

	w/o constant & trend	Lag	w/constant	Lag	w/constant & trend	Lag
China	-2.091^{**}	5	-0.201	4	-2.478	0
Indonesia	-1.182	4	-0.491	3	-1.66	3
India	-1.941^{*}	3	1.074	0	-1.138	12
Myanmar	-0.473	0	-2.39	0	-3.406^{*}	0
Philippines	-1.700^{*}	0	-1.331	1	-1.137	8
Taiwan	-1.189	5	0.268	6	-1.408	4
Thailand	-2.649^{***}	1	-1.901	6	-1.615	0

Note: The percentiles of the probability distribution of the test statistic are sourced from Fuller (1996, Table 10.A.2).
***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 1b
DF-GLSu test results.

	w/constant	Lag	w/constant & trend	Lag
China	-0.913	5	-3.532^{*}	4
Indonesia	-0.896	4	-2.369	4
India	0.298	3	-1.492	3
Myanmar	-2.395	0	-2.538	0
Philippines	-1.693	0	-2.704	0
Taiwan	-0.857	5	-2.261	5
Thailand	-0.977	6	-1.605	6

Note: The percentiles of the probability distribution of the test statistic are sourced from Fuller (1996, Table 10.A.2). * denotes statistical significant at the 10% level.

Table 1c
KPSS results (with constant).

	$p = 0$	$p = 2$	$p = 4$
China	0.229^{***}	0.092	0.066
Indonesia	1.085^{***}	0.420^{***}	0.284^{***}
India	1.756^{***}	0.652^{***}	0.419^{***}
Myanmar	0.426^{***}	0.163^{**}	0.111
Philippines	1.302^{***}	0.497^{***}	0.325^{***}
Taiwan	1.149^{***}	0.405^{***}	0.256^{***}
Thailand	1.051^{***}	0.378^{***}	0.247^{***}

Note: The percentiles of the probability distribution of the test statistic are from Kwiatkowski et al. (1992). p denotes the bandwidth. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Table 1d
KPSS results (with constant & trend).

	p = 0	p = 2	p = 4
China	9.978^{***}	3.437^{***}	2.117^{***}
Indonesia	6.365^{***}	2.306^{***}	1.472^{***}
India	9.653^{***}	3.347^{***}	2.067^{***}
Myanmar	0.940^{***}	0.357	0.240
Philippines	9.003^{***}	3.135^{***}	1.929^{***}
Taiwan	8.612^{***}	2.997^{***}	1.862^{***}
Thailand	7.337^{***}	2.519^{***}	1.554^{***}

Note: The percentiles of the probability distribution of the test statistic are from Kwiatkowski et al. (1992). p denotes the bandwidth. *** denotes statistical significance at the 1% level.

Lumsdaine and Papell (1997).[7] Table 2 provides the test results. For the Philippines and Thailand, the rejection of the null is significantly confirmed in either tests with one or two breaks for the cases w/constant and w/constant & trend. This result means that the CO2 emissions levels of the Philippines and Thailand relatively converge to or catch up with the US level, though their trend paths are kinked. We also see the catching-up trend for Indonesia and Taiwan because their results for w/constant & trend are significant.

4.3. Covariate ADF unit root test with structural breaks

We apply the CADF tests with/without breaks to obtain more insights into Asian economies' CO2 emission behaviours.[8] We use two stationary covariates, population (log) and real per capita GDP growth, for the tests.[9] The population of a country represents the level of citizens' daily activities. Per capita GDP is a value added measured per person produced through economic activities. Since these social and economic activities captured by the stationary covariates seem to reflect the magnitude of energy consumption, we expect these stationary covariates to covariate with CO2 emissions and thus raise the power of the CADF tests.

From Table 3, the results show the significant rejections of the null for w/o constant & tend for China, India, Taiwan and Thailand for both covariate cases and for the Philippines for the real per capita GDP covariate case. This result may suggest a trend of absolute convergence of CO2 emissions to the US for these countries. However, one unresolved issue remains: the over-rejection of the null due to the omission of existing structural breaks. This unresolved issue also holds for the other results in this test. We will discuss this issue later in this section. In addition, as Fig. 2 shows, all the difference series are above zero on the horizontal axis, suggesting that the countries continue to move toward the long-run equilibrium in per capita CO2 emissions relative to that of the US. Therefore, we withhold conclusions regarding the existence of historical long-run absolute convergence. In Table 3, the test also supports weak but significant evidence of catching-up for Indonesia because the unit root null is rejected for the case of w/constant & trend when we use population as a covariate. Myanmar has clear tendencies of relative convergence and/or catching-up because the results reject the null for w/constant and w/constant & trend. We need to confirm the reliability of these results by comparing them to the results of tests with breaks.

When we consider one endogenous structural break, Table 4 indicates that from the rejection of the null for w/constant & trend, the catching-up process holds for Indonesia, the Philippines, Taiwan and Thailand for both covariates, and for Myanmar for the population covariate. Relative convergence is supported for the Philippines for both covariates and for Indonesia, Myanmar, Taiwan and Thailand for the population covariate. Taiwan also indicates absolute convergence for the population covariate even when the test allows for a structural break. Using the CADF test with two structural breaks, the results in Table 5 show very similar catching-up and convergence tendencies to those of Table 4. Moreover, the catching-up effect is significant for China when using the population covariate. This two-break case nullifies the significance of relative convergence for Myanmar for the population covariate.

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[7] We also conducted the tests proposed by Perron and Vogesland (1992) and Papell and Prodan (2006). The results are analogous to those of Table 2. However, these tests do not consider a regression model without a constant; therefore, they are omitted.

[8] The non-parametric estimator is used to obtain the consistent estimator of ρ^2, following Hansen (1995):

$$\widehat{\rho}^2 = \frac{\widehat{\sigma}_{ve}^2}{\widehat{\sigma}_v^2 \widehat{\sigma}_e^2}$$

where

$$\widehat{\sigma} = \begin{pmatrix} \widehat{\sigma}_v^2 & \widehat{\sigma}_{ve} \\ \widehat{\sigma}_{ve} & \widehat{\sigma}_e^2 \end{pmatrix} = \sum_{k=-M}^{M} w\left(\frac{k}{M}\right) \frac{1}{T} \sum_t \widehat{\eta}_{t-k} \widehat{\eta}'_t$$

and $\widehat{\eta}_t = (\widehat{v}_t\ \widehat{e}_t)'$ is the least squares estimate of the error terms v_t and e_t from Eqs. (5) and (6), respectively. The Bartlett kernel is employed as a kernel weight function $w(\cdot)$, and the bandwidth M is determined based on the selection rule given by Andrews (1991).

[9] Both population and real per capita GDP are obtained from the Maddison Project database. The data of real per capita GDP except for India have some missing observations. We interpolated the missing values by estimating a polynomial function with order 3. In addition, we interpolated the data by estimating a polynomial function with order 2 and spline functions with orders 2 and 3. The results using these interpolated data are mostly the same.

Table 2
Results of Zivot and Andrews (1992) and Lumsdaine and Papell (1997) tests.

Countries	One break						Two breaks								
	(Zivot and Andrews, 1992)						(Lumsdaine and Papell, 1997)								
	w/o constant & trend		w/constant		w/constant & trend		w/o constant & trend			w/constant			w/constant & trend		
	min t	break	min t	break	min t	break	min t	break 1	break 2	min t	break 1	break 2	min t	break 1	break 2
China	−2.048	2002	−2.599	1949	−3.018	1951	−2.614	1943	1949	−4.068	1949	2002	−5.409	1943	1949
Indonesia	−1.180	1933	−2.082	4977	−6.189***	1942	−2.603	1941	1948	−2.545	1942	1975	−7.045***	1944	1948
India	−1.788	2002	−0.238	1983	−3.175	1939	−1.773	2000	2002	−1.654	1949	1980	−4.554	1940	1967
Myanmar	−0.532	1960	−4.103	1952	−4.322	1951	−0.542	1960	1992	−4.260	1952	1994	−4.353	1950	1987
Philippines	−1.805	1966	−7.185***	1947	−8.265***	1947	−2.361	1929	1943	−8.712***	1942	1943	−9.157***	1947	1959
Taiwan	−1.170	2002	−1.844	1975	−5.216**	1942	−2.697	1942	1948	−2.382	1958	1975	−6.648**	1942	1975
Thailand	−2.660	1951	−3.887	1950	−13.857***	1950	−3.220	1951	1952	−5.935**	1950	1987	−13.888***	1950	1971

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of the asymptotic distribution of the test, respectively. The percentiles of the probability distributions of both tests for w/constant & trend are from Zivot and Andrews (1992) (Model A) and Lumsdaine and Papell (1997) (Model AA). Those for other cases are from Matsuki (2019, Table A2)

Table 3
Results of the CADF test without break (Reference country: US)

Countries	Covariate: Population						Covariate: real per capita GDP growth					
	w/o constant & trend		w/constant		w/constant & trend		w/o constant & trend		w/constant		w/constant & trend	
	t	ρ^2	t	ρ^2	t	ρ^2	t	ρ^2	t	ρ^2	t	ρ^2
China	−2.053**	0.96	−2.086	0.45	−2.446	0.98	−2.522***	0.74	−1.327	0.83	−1.365	0.89
Indonesia	−1.313	0.97	−1.780	0.78	−1.978*	0.06	−1.532	0.87	−1.060	0.85	−1.573	0.87
India	−2.587***	0.84	−0.563	0.57	−0.671	0.71	−2.423**	0.93	−0.373	0.84	−1.347	0.97
Myanmar	−0.556	0.97	−3.497***	0.74	−3.916***	0.02	−0.542	0.72	−2.461*	0.68	−2.134	0.70
Philippines	−1.581	1.00	−0.964	0.95	−0.130	0.01	−1.903*	0.91	−1.891	0.88	−1.498	0.91
Taiwan	−1.885*	0.88	−1.329	0.76	−0.676	0.61	−2.056**	0.74	−0.478	0.73	−0.380	0.71
Thailand	−2.362**	1.00	−1.636	0.62	−1.595	0.58	−2.811***	0.97	−2.175	0.95	−1.964	0.93

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The percentiles of the probability distribution of the test statistic are displayed in Hansen (1995, Table 1).

Table 4
Results of the CADF test with one endogenous break (Reference country: US)

Countries	Covariate: Population								
	w/o constant & trend			w/constant			w/constant & trend		
	t	ρ^2	break	t	ρ^2	break	t	ρ^2	break
China	−2.707	0.42	1960	−3.345	0.47	1949	−3.125	0.42	1949
Indonesia	−3.004	0.52	1939	−5.786***	0.07	1942	−6.041***	0.12	1942
India	−2.501	0.74	1992	−1.039	0.23	1967	−2.324	0.10	1940
Myanmar	−1.935	0.50	1972	−4.348*	0.87	1951	−4.650**	0.00	1973
Philippines	−2.147	0.62	1966	−8.408***	0.35	1947	−6.250***	0.26	1947
Taiwan	−4.944***	0.08	1941	−4.555**	0.06	1942	−4.753**	0.26	1941
Thailand	−2.499	0.26	1969	−9.958***	0.00	1950	−11.634***	0.04	1950
	Covariate: Real GDP growth								
Countries	w/o constant & trend			w/constant			w/constant & trend		
	t	ρ^2	break	t	ρ^2	break	t	ρ^2	break
China	−2.856	0.68	1960	−2.824	0.87	1949	−2.047	0.96	1949
Indonesia	−1.951	0.83	1935	−2.269	0.85	1975	−6.287***	0.96	1942
India	−2.193	0.94	1997	−0.458	0.84	1964	−3.642	0.90	1939
Myanmar	−1.390	0.62	1992	−3.168	0.74	1952	−2.786	0.72	1952
Philippines	−2.087	0.89	1948	−8.576***	0.58	1943	−8.316***	0.92	1947
Taiwan	−2.032	0.74	2002	−1.450	0.73	1975	−4.805**	0.66	1944
Thailand	−2.975	0.93	1951	−3.924	0.98	1950	−13.917***	0.96	1950

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The percentiles of the probability distribution of the test statistic for w/o constant & trend and w/constant are displayed in Matsuki (2019, Table A4). Those for w/constant & trend are displayed in Table A1.

Table 5
Results of the CADF test with two endogenous breaks (Reference country: US)

Countries	Covariate: Population											
	w/o constant & trend				w/constant				w/constant & trend			
	t	ρ^2	break 1	break 2	t	ρ^2	break 1	break 2	t	ρ^2	break 1	break 2
China	−3.829	0.12	1960	1983	−4.011	0.53	1949	2002	-5.223^{*}	0.32	1945	1949
Indonesia	−3.644	0.17	1940	1983	-6.976^{***}	0.04	1944	1948	-7.003^{***}	0.56	1944	1948
India	−2.543	0.16	1964	1992	−1.584	0.27	1940	1946	−3.557	0.17	1940	1967
Myanmar	−2.962	0.23	1972	1987	−4.379	0.67	1951	1987	-5.425^{**}	0.00	1973	2004
Philippines	−2.391	0.40	1966	1995	-9.151^{***}	0.47	1947	1959	-9.050^{***}	0.01	1947	1977
Taiwan	-5.315^{***}	0.04	1934	1942	-5.114^{**}	0.05	1942	1975	-5.927^{**}	0.24	1934	1944
Thailand	−2.761	0.08	1957	1969	-14.731^{***}	0.04	1950	1993	-15.452^{***}	0.02	1950	1974
	Covariate: Real GDP growth											
Countries	w/o constant & trend				w/constant				w/constant & trend			
	t	ρ^2	break 1	break 2	t	ρ^2	break 1	break 2	t	ρ^2	break 1	break 2
China	−3.304	0.85	1945	1949	−3.596	0.94	1949	2002	−4.725	1.00	1945	1949
Indonesia	−2.640	0.97	1942	1947	−2.871	0.83	1942	1975	-6.998^{***}	1.00	1944	1948
India	−2.199	0.95	1998	2002	−1.747	0.98	1949	1980	−5.097	0.86	1939	1967
Myanmar	−1.400	0.61	1992	1999	−3.431	0.83	1949	2004	−2.782	0.73	1952	1987
Philippines	−2.558	0.92	1929	1943	-9.007^{***}	0.53	1943	1984	-9.487^{***}	0.89	1947	1959
Taiwan	−2.670	0.80	1944	1947	−1.971	0.70	1974	1988	-6.012^{**}	0.70	1934	1944
Thailand	−3.149	0.88	1951	1995	-6.350^{***}	0.97	1950	1989	-14.841^{***}	0.97	1950	2003

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The percentiles of the probability distribution of the test statistic for w/o constant & trend and w/constant are displayed in Matsuki (2019, Table A4). Those for w/constant & trend are displayed in Table A1.

Table 6
Summary of the test results.

Tests	Absolute convergence	Relative convergence	Catching-up
Zivot and Andrews (1992)		Philippines	Indonesia, Philippines, Taiwan, Thailand
Lumsdaine and Papell (1997)		Philippines, Thailand	Indonesia, Philippines, Taiwan, Thailand
CADF	China (POP, GDP), India (POP, GDP), Philippines (GDP), Taiwan (POP, GDP), Thailand (POP, GDP)	Myanmar (POP, GDP)	Indonesia (GDP), Myanmar (POP)
CADF with one break	Taiwan (POP)	Indonesia (POP), Myanmar (POP), Philippines (POP, GDP), Taiwan (POP), Thailand (POP)	Indonesia (POP, GDP), Myanmar (POP), Philippines (POP, GDP), Taiwan (POP, GDP), Thailand (POP, GDP)
CADF with two breaks	Taiwan (POP)	Indonesia (POP), Philippines (POP, GDP), Taiwan (POP), Thailand (POP, GDP)	China (POP), Indonesia (POP, GDP), Myanmar (POP), Philippines (POP, GDP), Taiwan (POP, GDP), Thailand (POP, GDP)

Note: Appearance of the country name indicates significant catching-up or convergence. The words in the parentheses are covariates corresponding to the displayed results, i.e. POP and GDP denote population and real per capita GDP growth, respectively.

The detected break dates also provide firm facts of changing points in the CO2 emission patterns in Asian economies: 1945 and 1949 for China, 1944 and 1948 for Indonesia, 1951 for Myanmar, 1943 and 1947 for the Philippines, 1934 and 1944 for Taiwan and 1950 for Thailand. Overall, these break dates correspond to those in Table 2. For China, the first break date (1945) captures the economic instability around the end of World War II, which resulted in sharp declines in production as well as CO2 emissions. The second break date (1949) coincides with the initial stage of economic recovery achieved by the establishment of China in 1949, which led to significant changes in the social and economic systems. These changes affected people's daily lives and companies' economic activities considerably. Some of these impacts may reflect the CO2 emission pattern.[10] Indonesia experienced a war for independence against the Netherlands in 1945–1949. The obtained break dates correspond to this period. After Myanmar's establishment in 1948, the first general election was held in 1951; intensified fractional conflicts in the ruling party then created political instability. The Philippines declared independence in 1943 and was released from Japanese rule in 1945. The data may capture the influences of these events and the subsequent social upheavals. In 1934, under Japanese rule, Taiwan started to operate Sun Moon Lake hydroelectric power plant No. 1 (Daguan power plant), which was the largest hydroelectric power plant in Asia. It increasingly promoted industrialisation, particularly in the electrochemical industry, which is a possible CO2 emission driver (Kobayashi, 1973). In 1945, Taiwan was released from Japanese rule and governed by the Chinese National party. The estimated break dates occur around this event. In 1950, Thailand established the predecessor of the National Economic and Social Development Board to formulate economic development plans. Since then, it experienced recovery periods in the 1950s and 1960s. This experience matches the break date.

Table 6 summarises the test results. For Indonesia, Myanmar, the Philippines and Thailand, we obtain robust evidence to support catching-up and relative convergence. In terms of their CO2 emissions,

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[10] Although the difference between total per capita CO2 emissions in the US and China depends on the fluctuations in total per capita CO2 emissions within these two countries, the Chinese data fluctuations clearly reflect the occurrences of breaks in the data. In addition, the population and per capita real GDP growth used as stationary covariates may affect the break date estimation results to some extent. These original data are available from the authors upon request.

these countries are in the catching-up process or long-run convergence state, maintaining a certain distance from the US. CO2 emissions in these countries are converging toward the US for several reasons. First, demand for coal in these countries is driven by the absence of low-carbon technology breakthroughs and its low cost compared with cleaner-burning natural gas and renewable energy. According to the International Energy Agency (IEA) data,[11] Indonesia is the world's fifth-largest coal producer and second-largest net exporter, while Thailand is the ninth-largest net importer. Their increasing reliance on coal and fossil fuels leads to faster increases in CO2 emissions than anywhere else between 1990 and 2010. Deforestation is another major source of CO2 emissions in the region. In Indonesia, home to the world's largest forest lands, trees are cut down to feed a growing population and to produce paper and palm oil, which are the main sources of export revenue. The third reason is policy conflicts. Although these countries set national goals for reducing fossil fuel use, the goals conflict with policies to subsidise the cost of petroleum products to benefit the poorest citizens. Such subsidies boost fuel demand and crowd-out clean energy, they are also estimated to cost governments more than it would take to meet the region's Paris Agreement goals. We should also note that the CADF tests with/without breaks can only detect this fact for Myanmar and obtain more rigorous results for Thailand. This is also true for Taiwan. The CADF tests show all three types of convergence and catching-up tendencies, which seem to display stepwise phases of converging to the US during the sample period. We also see the catching-up tendency for China. This is a natural consequence because China's economic output has been catching up with that of the US. Moreover, around 20 million people move from rural to urban areas in China each year for better jobs and more comfortable lifestyles. The mass movement of people is threatening China's goal of CO2 emissions abatement. As Wiedenhofer et al. (2017) argue, since people moved from rural to urban areas, they have increasingly aspired to live westernised lifestyles that are resource and carbon intensive.

Although the CADF test without breaks implies absolute convergence for five countries, as the gaps of their differences remain positive in Fig. 2, we should view this finding cautiously since over-detections may occur due to the omitted structural breaks. Our cautious interpretation may be supported because the CADF tests with breaks show absolute convergence for only one country (Taiwan) when we consider one or two structural breaks.[12] In light of this concern, it is better to withhold conclusions on the existence of historical long-run absolute convergence over the whole sample period for these countries except for Taiwan. To fully disentangle this issue, more information is needed. This is true for India, which is detected by only one test. However, India's economy has been rapidly chasing developed countries' economies through its own economic strategies. This caused the decreasing trend in the difference in CO2 emissions between India and the US. We certainly need more information to draw conclusions.

5. Conclusions and policy recommendations

This study investigates whether the per capita CO2 emissions of seven Asian economies (China, Indonesia, India, Myanmar, the Philippines, Taiwan and Thailand) are catching up with or converging toward that of the US in the long run. Since we suspect that our historical CO2 emission data (the sample ends in 2011) have some structural breaks, we applied several unit root tests that allow for endogenous structural breaks. These tests include more powerful covariate unit root tests with structural breaks. Interestingly, we found that six of the seven countries show some tendencies of catching-up or absolute/relative convergence toward the US. Indonesia, Myanmar, the Philippines and Thailand have catching-up and relative convergence trends toward the US, while Taiwan absolutely converges after experiencing several converging phases such as catching-up and relative convergence. In addition, China is at least in a catching-up process. Although the issue of over-detection of absolute convergence remains for some countries, most of the test results are plausible. The historical and economic backgrounds of these countries seem to justify our results.

Given our findings, we can suggest the following policy recommendations to improve the convergence of carbon emissions and to achieve emissions reduction targets. First, the CO2 emissions of Asian economies with different development levels converging toward the US are associated with the United Nation's sustainable development goals. Countries need to continuously implement energy-saving and emission reduction policies in the future. Second, real per capita GDP and population are the key factors in the convergence of CO2 emissions in developing Asia. Hence, to ensure stable CO2 emissions, the economic growth rate should be moderated rather than over-emphasised. Moreover, reducing the population density in countries such China and India can help reduce per capita CO2 emissions. Third, greater efforts need to be made to reduce the use of traditional fossil energy and develop clean renewable energy. When Asian economies set their carbon emissions reduction targets, they must consider not only economic development levels but also the steady-state value of the final convergence of per capita CO2 emissions of all countries in the world.

Our study has one potential limitation. We did not analyse the data of other developing countries. However, growing economies are striving to achieve developed country living standards and longevity, which require more energy use, and hence tend to increase CO2 emissions at higher rates compared to matured economies. Therefore, future research should include more countries to discuss this topic more thoroughly.

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Declaration of Competing Interest

The authors declare no conflict of interest.

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[11] The data are available online at: https://www.iea.org/publications/freepublications/publication/KeyWorld2017.pdf

[12] Another possible interpretation is that the test may detect the most recent rapid decreasing trend toward the US as absolute convergence, even if there are still large gaps between Asian countries and the US.

Appendix A. Appendix

Table A1
The percentiles of the asymptotic distributions of the CADF test with breaks.[a]

Number of breaks	ρ^2	1%	5%	10%
One break [b]	0.99	−5.33	−4.83	−4.57
	0.9	−5.28	−4.79	−4.54
	0.8	−5.30	−4.79	−4.52
	0.7	−5.26	−4.75	−4.49
	0.6	−5.25	−4.74	−4.46
	0.5	−5.20	−4.70	−4.42
	0.4	−5.16	−4.65	−4.38
	0.3	−5.11	−4.59	−4.33
	0.2	−5.07	−4.53	−4.26
	0.1	−4.98	−4.45	−4.17
Two breaks [c]	0.99	−6.31	−5.78	−5.54
	0.9	−6.27	−5.76	−5.50
	0.8	−6.19	−5.73	−5.48
	0.7	−6.15	−5.72	−5.45
	0.6	−6.11	−5.66	−5.41
	0.5	−6.08	−5.61	−5.36
	0.4	−6.07	−5.55	−5.29
	0.3	−6.05	−5.49	−5.22
	0.2	−5.98	−5.43	−5.15
	0.1	−5.89	−5.34	−5.06

[a] The regression model includes both a constant term and time trend.

[b] The percentiles are obtained from the empirical distribution for $T = 1000$, and the number of replications is 50,000.

[c] The percentiles are obtained from the empirical distribution for $T = 500$, and the number of replications is 3000.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105326.

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