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A historical perspective with new concepts

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Convergence of oil consumption: A historical perspective with new concepts

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Abstract
Growing concerns about long-run equilibrium in the oil market have focused on understanding the time path of oil consumption across countries. This study examines the convergence of oil consumption across the largest oil consumers. To this end, we employ the historical oil consumption data dating back to 1890 by benefiting from the newly proposed convergence concepts, including relative/club convergence and weak σ-convergence, in addition to the conventional β-convergence notion. The empirical results provide new and insightful findings.

1. Introduction
In recent decades, worldwide oil consumption has increased dramatically with a boom from 8588.9 (in 1995) million tonnes of oil equivalent to 13,147.3 as of 2015. The use of oil is projected to increase as the world grows (BP, 2018). Importantly, the Energy Information Administration (EIA) forecasts the current statistics of global oil consumption as 3.6 million barrels per capita per day in 2022 and 1.8 million barrels per capita in 2023, reaching 100.5 million barrels per capita in 2022 and 102.3 million of barrel per capita in 2023 (EIA, 2022). This oil consumption pattern has been considered a major cause of global warming and greenhouse gas emissions, mainly because of the direct release of carbon dioxide (CO₂) emissions into the atmosphere (Kay et al., 1996; Magazzino et al., 2021). Correspondingly, the global community of scholars and policymakers has started examining oil consumption dynamics. In that pursuit, the convergence characteristics of energy consumption among countries have been at the center of discussion of environmental sustainability and energy security in the energy economics literature (Apergis and Payne, 2010; Bulut and Dursus-Ciftci, 2018; Kounetas, 2018; Soytas et al., 2007).

Economic convergence is based on the catching-up hypothesis in growth theory. Economies move towards their steady-state in the long run. Hence, developing countries can catch up with the developed world. Studies on the convergence of energy consumption have emerged from this mainline (Akram et al., 2020). In this paper, we consider convergence patterns in oil consumption. Strong convergence in oil consumption implies movement towards a steady state. Hence, energy and environmental policies must work similarly across countries. It also means an individual country’s oil consumption level can be better predicted using other countries’ consumption behavior (Fallahi, 2017). On the other hand, weak or no convergence calls for different tools to...
reduce emissions and maintain energy security across countries. Information on other countries’ energy consumption levels will not improve forecasts of diverging oil consumption (Payne et al., 2017). Given oil’s strategic role for environmental sustainability and macroeconomic stability, examining the convergence of historical oil consumption will bring new insights concerning the influence of various oil, economic and financial crises, and wars on oil consumption patterns. While energy intensity has been decreasing lately, oil consumption is typically increasing, and the convergence pattern of oil consumption may differ (Dargay and Gately, 2010). Since oil consumption data are critical in curbing CO₂ emissions, analyzing oil consumption dynamics will shed new light on the efficacy of policies to curb carbon dioxide emissions during the last century.

The previous studies mainly focus on the convergence hypothesis of energy consumption, coal consumption, natural gas consumption, and renewable energy consumption. Surprisingly, much less attention has been given to oil consumption convergence. This study aims to fill this gap and provide relevant policy orientation about the effectiveness of adopted energy conservation policies in developed countries to meet the global energy structure stated under the Paris Agreement.

Our motivation to explore the convergence of oil consumption per capita lies in three key insights. First, the knowledge of the convergence characteristics of oil consumption will guide policymakers in designing comprehensive energy policies over a long-time span. Convergence suggests conservation and demand management strategies (such as tariffs on imported oil and taxes on the use of oil) are less efficient in the long run because oil consumption will gradually adjust towards its steady-state (Hao et al., 2015; Meng et al., 2013; Payne et al., 2017). Second, convergence in oil consumption would allow for the design of appropriate tools and mechanisms to facilitate energy policy coordination and cooperation across countries. Effectively, the catching-up effect of convergence in oil consumption suggests that the oil consumption gap can be narrowed as countries with initially higher levels of oil consumption can formulate effective energy efficiency policies (Wu et al., 2018; Zhu and Lin, 2020). Thirdly, the convergence of oil consumption is important in predicting the future course of oil demand and improving a country’s energy structure. In this light, investors and oil market participants can use the past trend of oil consumption to forecast oil demand.

The purpose of this study is to examine the convergence of oil consumption across the most prominent oil consumers. To do so, we provide a new and unique look at the characteristics of historical oil consumption in 16 advanced countries, using newly proposed convergence concepts, including relative/club convergence and weak σ-convergence, in addition to the conventional β-convergence notion. The empirical results provide new and insightful findings. First, considering common factors in the dynamics of oil consumption leads to the convergence of oil consumption. Second, absolute convergence has been at work among countries mainly before the great depression 1890–1929, while divergence occurs after the mid of 1960s. Third, the divergence observed over the last decades persists even after accounting for relative or weak forms of convergence, supporting the main role of the current dynamics in world oil markets in divergence patterns. Moreover, the clustering algorithm identifies unique convergent clubs, indicating that a unified energy policy is not tenable globally.

The contributions of our study are also multifold. The use of an extended historical oil consumption dataset is one of the key aspects of our study. We employ data covering 1870 to 2017 for the most significant oil consumers. In doing so, our analysis provides a historical perspective on the behavior of oil consumption that previous studies are lacking in the current literature. Most empirical studies start from the 1980s or later. The conflicting results in the empirical literature can be attributed to the lack of consistent data over a long period and the estimation techniques that test only for the presence of long-run persistence in energy rather than oil consumption.

Second, in addition to the conventional β-convergence notion, we test for the new concepts of convergence, namely the relative and club convergence proposed by Payne et al. (2017, 2009) and the weak σ-convergence by Kong et al. (2019). As well established, the convergence parameter is assumed to be homogeneous in the β-convergence definition. The literature on the convergence properties of energy consumption is championed by the influential paper of Narayan and Smyth (2007). Since this pioneering work, a series of papers, have evolved using applied unit root and cointegration tests to test stochastic convergence in energy consumption. For example, Ozcan (2013) uses univariate panel LM (Lagrange multiplier) unit root tests to study the stochastic convergence of energy consumption in 17 MENA countries over 1980–2009.

By using LM and residual augmented least squares (RALS)-LM tests, Payne et al. (2017) find out convergence in per capita renewable energy consumption across US states; Cai and Menegaki (2019) provide support for convergence of clean energy consumption in several OECD countries, Akram et al. (2020) reveal evidence of convergence for energy consumption categories. More recently, Ahmed Qahtan et al. (2021) indicated strong evidence for stochastic convergence in renewable and non-renewable energy consumption in oil-exporting and importing nations in the MENA region. The extant empirical studies do not provide unanimously strong results. As pointed out in Kassouri (2022), this can partly be explained by the fact that oil consumption follows a more complex (hybrid) pattern, which conventional methods cannot effectively capture. This study adds to the literature by employing a recent methodology to account for weak convergence, convergent clubs, and cross-sectional dependence among countries.

Last but not least, we further examine the convergence of oil consumption for the sub-samples to shed light on whether convergence patterns change over time. To the best of our knowledge, this is the first study providing a fragmented analysis of oil consumption convergence over different sub-periods. This analysis allows us to capture the possible heterogeneity in the dynamics of oil consumption because oil consumption has been subject to a wide range of external shocks (Kassouri et al., 2022). This study is thereby expected to be insightful for scholars and policymakers trying to understand the impacts of various shocks on oil consumption to predict the pattern of oil demand.

2. Overview of domestic energy policies

Besides external shocks related sometimes to the constraining power of international treaties (as the Kyoto Protocol adopted in 1997 and the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC) established in 2015), domestic energy and environmental policies are without doubt one of the most important triggers of oil consumption paths. The main reason for considering domestic policy is that in the past, energy policies were mainly made at the nation-state level. Even today, adopting a common energy policy across countries and/or economic areas is key in driving oil consumption patterns.

The Scandinavian countries (Denmark, Norway, and Sweden) have put a lot of effort into developing alternative energy and trying to minimize the share of hydrocarbons in their economies to the least possible level. For instance, Denmark was the original pioneer in wind energy (Lipp, 2007; Mendonça et al., 2009). Consequently, wind power has been the central element of Danish renewable energy policy. However, public support has also been given to the development of, for example, biogas and solar collectors. Wind power was already a factor of three higher than the coverage in Germany and Spain and an order of magnitude higher than any other nation in 2003 (Meyer, 2004). It is expected to cover about 55% of Danish electricity consumption in 2030. These policies have been developed to decrease Danish dependence on fossil fuels. Norway and Sweden have historically had access to significant hydropower resources, which has led to the development of an electricity-intensive industry structure and cheap electricity for residential consumers (Unander et al., 2004). However, Sweden had
exploited most of its hydropower potential by 1970 and instead began developing nuclear power. After a referendum in 1979, Sweden decided to phase out its nuclear power generation. Nuclear power has dominated the Swedish energy debate for more than two decades, and the schedule for the phasing-out has been delayed several times. Norway and Sweden have about 70% of the European hydro reservoir capacity and remain highly interconnected to northern Europe. However, today access to new hydro-based energy is limited due to climate change. Policymakers in these countries are increasingly supporting the development of energy efficiency and new renewable energy projects, including a nuclear shutdown, a cancellation of local hydropower, and an expansion of export capacity to Europe (Seljom and Tomasgard, 2017). These environmental and energy policy actions on the energy systems in these countries have substantially shaped fossil fuel consumption in these countries.

The EU can be considered a net-importer zone, especially the largest EU countries (Germany, France, and Italy). Energy policy intends to decrease their dependence on fossil fuels—predominantly oil and natural gas—to ensure their energy supply security to avoid third-country pressure. In 2009, the European Union (EU) established a new common framework for the promotion of energy (both electrical and thermal) from renewable sources to increase by 20% renewable energy in their energy consumption by 2020 (European Commission, 2020; European Environment Agency, 2018a). Establishing a common energy policy target by member states can lead to a similar pattern in their energy consumption, which in turn may lead to a convergence trend in oil consumption. Unlike Scandinavian countries, the harmonization of energy policy within the EU can lead to convergence in oil consumption.

Over past decades, federal and state governments in the US have established numerous policies to decrease their level of consumption of fossil fuels, including renewable energy technologies (wind, solar, biofuels, and electric vehicles), carbon-pricing systems, financial incentives, and tax policies such as electric vehicles tax credits, investment tax credit, the renewable fuel standard. While policymakers were not in agreement about what policy programs would be the best alternative or what goals the programs were to achieve in terms of addressing energy security, the US oil imports have been cut in half over the past decade (Greene and Liu, 2015).

This overview of domestic energy policy across countries motivates us to inquire whether the convergence process in oil consumption is global or local and to examine the possibility of a concurrent oil consumption club’s formation across economic areas. This is why we use sophisticated econometric techniques to account for various convergence perspectives in our oil consumption paths.

3. Theoretical background and testing methods

3.1. $\beta$-Convergence

We begin with the concept of $\beta$-convergence in the spirit of Baumol (1986), implying that countries with high initial oil consumption levels have a lower consumption growth rate than countries with low initial levels of oil consumption. $\beta$-convergence allows examining the catching-up effect in oil consumption. Within a panel data framework, $\beta$-convergence can be examined based on the following specification:

$$\Delta y_{it} = \alpha_i + \beta y_{i,t-1} + \gamma \pi_{it} + \xi_{it}$$

where $\Delta$ is the first-difference operator, $y_{it}$ is the oil consumption of country $i$ at time $t$, $i = 1, \ldots, N$ denote cross-section dimension, $t = 1, \ldots, T$ denote time dimension, $\alpha_i$ captures individual fixed effects, and $\xi_{it}$ is the error term. This specification allows one to test the null hypothesis of $\beta = 0$ against the alternative hypothesis of $\beta < 0$. Thus, rejection of the null hypothesis supports the notion of absolute convergence with the speed of convergence given by transition parameter $\beta$.

The absolute $\beta$-convergence rests with the assumption that all countries follow the same-steady state for per capita oil consumption. If the steady-state in the long run is different across cross-sectional units in the panel, equation (1) becomes miss-specified, which leads to an inconsistent point estimate of $\beta$. To overcome this issue, some control variables affecting the long-run steady-state level are included in equation (1), and the conditional $\beta$-convergence is examined with the following augmented regression model:

$$\Delta y_{it} = \alpha_i + \beta y_{i,t-1} + \gamma \pi_{it} + \xi_{it}$$

where $\pi_{it}$ is per-capita income used as the control variable following the energy consumption and economic growth literature. In this framework, the null hypothesis of absolute convergence is given as $H_0: \gamma = 0$ and $\beta < 0$ against the alternative hypothesis of conditional convergence as $H_1: \gamma \neq 0$ and $\beta < 0$.

The dynamic panel data model defined in equation (2) may suffer from inconsistency and invalid statistical inference because the fixed effect estimation is inconsistent as $N$ increases for a fixed $T$ (Nickell, 1981) - known as the Nickell bias-arising from the correlation between regressors and regression errors. The solution for Nickell bias is to employ the generalized method of moments (GMM) estimator. The system GMM approach proposed by Blundell and Bond (1998) is widely used in the empirical literature to test for $\beta$-convergence.

The inconsistency and invalid statistical inference problems may also stem from cross-sectional dependence, implying that some common factors affect cross-sectional units in the panel. Hence, current efforts have focused on estimating the panel data models under cross-sectional dependence. The common factor representation of the regression error can be defined as $\xi_{it} = \lambda F_t + u_{it}$ where $F_t$ is a vector of unobserved common factors and $\lambda_i$ is a vector of factor loadings. The factor representation of equation (2) can be written as

$$\Delta y_{it} = \alpha_i + \beta y_{i,t-1} + \gamma \pi_{it} + \lambda F_t + u_{it}$$

which is called as common correlated effects (CCE) model of Pesaran (2006), which uses the cross-sectional averages of the dependent and independent variables $(\Delta y_{it}, \pi_{it}, \xi_{it})$ as the estimates of $F_t$. In more recent studies, Gaibulloev et al. (2014) and Chudik and Pesaran (2015), among others, discuss the estimation of dynamic panel data models under cross-sectional dependence and suggest the dynamic CCE.

3.2. Relative convergence

It is clear from either model (1) or (2) that transition parameter $\beta$ is assumed to be homogenous in the $\beta$-convergence definition. The relative convergence framework developed by Phillips and Sul (2007), hereafter PS, allows the idiosyncratic element to evolve over time, capturing cross-sectional heterogeneity with time-varying factor loadings. Therefore, we refer to the relative convergence concept to examine whether oil consumption across countries would converge to a common steady-state independent of their initial conditions. Furthermore, the PS method does not require pre-testing for unit root and/or cointegration because it does not impose any assumption related to trend stationarity or stochastic non-stationarity of the data and common factors across individuals in the panel.

The PS approach examines convergence concerning heterogeneous conditions following different paths.
time-varying idiosyncratic components by accounting for common components based on a non-linear transition factor model, given by

$$y_{it} = \delta_t \mu_i$$  \hspace{1cm} (4)

where $\delta_t$ denotes idiosyncratic component that captures time-varying individual specific effects, and $\mu_i$ represents common component that captures time-varying common factor in the data. Put it in other words, the idiosyncratic component $\delta_t$ is a measure of the share of common component $\mu_i$ in $y_{it}$ for each cross-section. Neither $y_{it}$ nor $\mu_i$, is restricted to be trend-stationary since equation (4) does not require stationarity or non-stationarity of either variable.

The idiosyncratic element is defined by

$$\delta_t = \delta_0 + \sigma_i \nu_i L(t)^{-1} r^a$$  \hspace{1cm} (5)

where $\delta_0$ is constant, $\nu_i \sim iid(0,1)$ $\forall i$ depend over time $t$, $L(t)$ is the penalty function that is a class of slowly varying function over time (i.e., $L(t) \to \infty$ as $t \to \infty$) and $a$ is the decay rate. Equation (5) implies that $\delta_t$ converges to $\delta_0$ for $a > 0$. Hence, the null hypothesis of convergence defined as $H_0: \delta_t = \delta_0$ and $a = 0$, is tested against the alternative hypothesis of divergence, $H_1: \delta_t \neq \delta$ for some $i$ and/or $a < 0$. To develop an empirical model to test the null hypothesis, PS first define the relative transition parameter, $h_{it}$, as

$$h_{it} = \frac{y_{it}}{N^{-1} \sum_{i=1}^{N} y_{it}} = \frac{\delta_0}{h_{it}}$$  \hspace{1cm} (6)

If the factor loadings $\delta_0$ converge to a constant, $\delta$, then the cross-sectional mean of the relative transition parameter $h_{it}$ converges to unity, and the variance of $h_{it}$ converges to zero as $t \to \infty$. Let $H_t$, is the variance of $h_{it}$, we thus have

$$H_t = \frac{1}{N} \sum_{i=1}^{N} (h_{it} - 1)^2 \to 0 \text{ as } t \to \infty.$$  \hspace{1cm} (7)

Equation (7) implies that the inverse variance ratio, $H_t / H_t$, will increase over time if the cross-sectional dispersion of $h_{it}$ or $\delta_0$ decreases over time. The increasing speed of $H_t / H_t$ is faster than the rate of divergence of the penalty function $L(t)$ under the convergence; but is slower under the divergence (see Sul, 2019). To distinguish convergence from divergence, PS define the following log-t regression model

$$\log \left( \frac{H_t}{H_t} \right) - 2 \log L(t) = a + b \log t + u_t$$  \hspace{1cm} (8)

where $L(t) = \log(t)$, $b = 2a$, and $t = |RT|$, $|RT| + 1, \ldots, T$ with $r > 0$. Since the log function is rapidly increasing initially, PS suggest eliminating the first third of the sample and recommend using $r = 0.3$. It is also worthwhile noting that since $u_t$ is serially correlated, PS employ the HAC (heteroscedasticity and autocorrelation consistent) long-run variance estimator proposed by Newey and West (1987). In the log-t regression model, the null of convergence is rejected if the t-ratio of $b \ (t < -1.65$ at the 5 percent level of significance.

3.3. Weak $\sigma$-convergence

The relative convergence concept, requiring the ratio of two series to converge to unity, in the long run, can explain convergence when series share common stochastic or deterministic trend components. This implies that the relative convergence does not hold when $y_{it}$ does not include a distinct (stochastic) trend. From the point of empirical view, testing the relative convergence is impossible as $y_{it}$ changes over time, or common factor $\mu_i$ does not contain any stochastic/non-stochastic trend (Sul, 2019; p. 120). Weak convergence captures convergence patterns when the common factor in oil consumption does not have a trend.

To capture convergent behavior in panel data with no stochastic or divergent trends, Kong et al. (2019, KPS hereafter) introduce the notion of weak $\sigma$-convergence, a concept defined in declining cross-sectional dispersion over time. KPS propose a simple-to-implement linear trend regression to test for the null of no weak $\sigma$-convergence, given by

$$K_t = a + qt + u_t$$  \hspace{1cm} (9)

where $K_t$ is the sample cross-sectional variance of $y_{it}$. KPS construct the t-statistic of the OLS estimate $\hat{\phi}$ by using the Newey and West HAC long-run variance estimator. In the linear trend regression model, the null of no weak $\sigma$-convergence is rejected if the t-ratio of $\hat{\phi} (t < -1.65$ at the 5 percent level of significance.

One important remark related to the notion of weak $\sigma$-convergence is that the pattern of $K_t$ depends on any possible common factors in $y_{it}$. A factor structure definition is $y_{it} = \delta_0 + \lambda_i F_t + u_{it}$ where $F_t$ is a vector of unobserved common factors and $\lambda_i$ is a vector of factor loadings, as previously defined. One can estimate $F_t$ with the method of principal components. Then, the common factor is eliminated by $\tilde{y}_i = y_{it} - \hat{\lambda}_i \hat{F}_t$ by keeping fixed effects $a_i$ in $\tilde{y}_i$; and the linear trend regression is estimated using $\tilde{y}_i$ instead of $y_{it}$.

4. Data

Our sample covers the period from 1890 to 2017, nearly a century and half of the oil consumption per capita for the sixteen largest oil consumers, including Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States. It is pretty appealing to focus on these countries because their level of oil consumption has the potential to significantly influence world oil prices and hence, global energy security and environmental policy.

The data are from the newly released CHDUPIN (Collection of Historical Data on the Uses of Petroleum International Network) research program, recently updated by Bergeaud and Lepetit (2020). The historical oil consumption data is available on the CHDUPIN website (http://www.longtermproductivity.com/chdupin/). It should be noted that Bergeaud and Lepetit (2020) rely on Astrid Kander et al. (2015) by extending the set of countries and using new data sources. This provides a unique long span of historical oil consumption data to bring new insights into the extant literature usually based on data from the 1980s. Historical oil consumption data helps us track the longest evolution of oil consumption and avoids the sample-size selection bias. In order to estimate the $\beta$-convergence model in (2), we also collect income per capita (Unander et al., 2004 PPP) from the project CHDUPIN website. We employ the natural logarithm of oil consumption and income per capita in our estimations.

Table 1 reports the descriptive statistics and results for the normality test for the 1890–2017 period. The highest average oil consumption is observed in the United States and Canada. These two countries also have the largest median, maximum, and minimum values and the smallest standard deviation with the United Kingdom. The skewness is negative in all countries, implying a left-tailed distribution. All the countries, but the Netherlands and the United States, have negative excess kurtosis (K < 3), which signals an existence of a platykurtic distribution. The JB normality test of Jarque and Bera (1987) indicates that the null of normality is rejected at 1 percent for all countries, providing evidence for non-Gaussian distributions of oil consumption.

Fig. 1 plots the dynamics of oil consumption. Three striking observations emerge. First, the visual inspection reveals some global tendencies. There has been a gradual increase in oil consumption since the early 1890s, with important fluctuations across countries. This suggests that the dynamics of oil consumption reflect the intensification of global factors (Casp et al., 2018). Second, these fluctuations have remained

2 The sample period and the countries are based on availability of the historical oil consumption data.
relatively high during the turbulent period 1890–1980, mainly due to several factors, including the great depression, World War II, and oil shocks during the 1970s (Hamilton, 2011; Rogoff, 2009). Third, the uppermost line plots the trend of oil consumption in the US, while the lowermost one plots that of Portugal. Overall, the dynamics of oil consumption have remained relatively stable since the 1980s. This points towards stability in oil consumption across countries over the last decades partly due to the coordination of energy policy to reduce their dependence on conventional fossil use through international climate agreements, including the Kyoto Protocol and the Paris Agreement.

5. Empirical results

It should be noted that our estimation strategy relies on a split-sample approach to disentangle heterogeneity over time in the convergence process of oil consumption. In addition to the whole period, we further examine the convergence of oil consumption for the sub-samples to shed light on whether convergence patterns change over time. The first sub-sample covers the period 1890–1929 before the great depression. This period was marked by World War-I and, after that, industrialization, especially in the US. So, demand-side factors were mainly driven by oil consumption during this period. As indicated in Hamilton (2011), oil production increased substantially in the US and Russia, resulting in a significant collapse in oil prices. The second sub-sample

Table 1
Descriptive statistics.

<table>
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<td>3.006</td>
<td>4.473</td>
<td>–0.667</td>
<td>1.582</td>
<td>–0.624</td>
<td>1.975</td>
<td>13.912</td>
</tr>
<tr>
<td>United States</td>
<td>USA</td>
<td>3.906</td>
<td>4.570</td>
<td>5.128</td>
<td>0.861</td>
<td>1.278</td>
<td>–1.143</td>
<td>3.009</td>
<td>27.887</td>
</tr>
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</table>

Med. is median, Max. is maximum value, Min. is minimum value, SD is standard deviation, S is Skewness, K is Kurtosis, JB is Jarque and Bera (1987) normality statistic, p-val. is probability of JB statistic. p-val < 0.01, 0.05, and 0.1 indicate significance at 1%, 5%, and 10%.

Fig. 1. Oil consumption (per capita, log).
includes the 1930–1969 recovery after the great depression. This period was marked by several events, such as the end of World War II and a transition to the automotive era. The US remained the key player in the world oil market, and oil prices were relatively stable during this period. However, the sharp transition to the automotive era resulted in important demand for oil, and the price of oil increased by 80% between 1947 and 1969 (Hamilton, 2011; Rogoff, 2009). The third sub-sample is from 1970 to 1993. During this period, there were instabilities in the oil market with several consequences on oil consumption; the age of OPEC was characterized by several oil shocks such as the 1973–1974 OPEC embargo, the Iranian revolution in 1978–1979, and the Iran-Iraq war in 1980, the Gulf War at the beginning of 1990s. The last sub-sample is for the 1994–2017 period of a new industrial age with the phenomenal growth in many East Asian economies characterized by growing oil consumption, mainly from China and South Korea.

Table 2 represents the results for the conditional \( \beta \)-convergence estimation. Note that the system GMM estimations should meet the validity of instrumental variables and the absence of second-order autocorrelation in the regression residuals. The Hansen statistics support the validity of the instrumental variables, and AR(2) test indicates that the second-order autocorrelation problem is insignificant. The coefficients on the lagged oil consumption, \( \hat{\beta} \), are negative but not statistically significant. Furthermore, the coefficients on the income, \( \hat{\gamma} \), are not statistically significant. The system GMM estimations imply that the \( \beta \)-convergence does not hold neither for the whole nor the sub-periods.

Caution with the system GMM estimations results is that this approach does not consider cross-correlations across the individuals. Ignoring potential cross-correlations may lead to inconsistency and invalid statistical inference. Before benefiting from the estimation with cross-sectional dependence, we test for the significance of cross-correlations with a battery of tests by using the LM (Lagrange Multiplier) test of Breusch and Pagan (1980), bias-adjusted LM test of Pesaran et al. (2008), and \( \text{CD}_{LM} \) and \( \text{CD} \) tests of Pesaran (2001). The cross-section dependence tests, reported in Table 2, reject the null hypothesis of no cross-sectional dependence at 1 percent for the whole and sub-periods, indicating significant cross-correlations across the largest oil-consuming countries.

Given the existence of cross-section dependence in the conditional \( \beta \)-convergence model, we employ the CCE model of Pesaran (2006). The results from the CCE approach, reported in Table 2, indicate that the lagged oil consumption and income have statistically significant coefficients with negative \( \hat{\beta} \) and positive \( \hat{\gamma} \) for the whole period, supporting the validity of the conditional \( \beta \)-convergence concept since \( \hat{\gamma} \neq 0 \) and \( \hat{\beta} < 0 \). For the 1890–1929 period, while the lagged oil consumption has a statistically significant negative coefficient, income is insignificant. This finding is consistent with the absolute \( \beta \)-convergence definition since \( \hat{\gamma} = 0 \) and \( \hat{\beta} < 0 \). This period marks the birth of the modern oil industry, fuel motors, the discovery of oil in the Middle East, and World War I, which established oil as a strategic commodity. Hence, it is not surprising to observe absolute convergence in this period. For the second (1930–1969), third (1970–1993), and fourth (1994–2017) sub-periods, \( \hat{\beta} \) is significantly negative and \( \hat{\gamma} \) is significantly positive, which is consistent with the conditional \( \beta \)-convergence. Historically, oil consumption increased with economic growth and is expected to converge across countries conditional on growth. As energy intensities and the share of fossil fuels in the energy mix decline, we expect convergence with a downward trend in oil consumption.

The results in Table 2 further indicate that the speed of adjustment (persistence) coefficients \( \hat{\beta} \) from the system GMM (which does not consider cross-sectional dependency) tend to be lower than those from the CCE (which considers cross-sectional dependency). This result indicates the importance of accounting for cross-correlation across countries to examine \( \beta \)-convergence. The persistence coefficient obtained from the CCE model is \( \hat{\beta} = -0.191 \) for the whole period, \( \hat{\beta} = -0.294 \) for the 1890–1929 period, \( \hat{\beta} = -0.470 \) for the 1930–1969 period, \( \hat{\beta} = -0.545 \) for 1970–1983, and \( \hat{\beta} = -0.582 \) for the 1994–2017 period. This result shows how convergence patterns of oil consumption growth in the largest oil-consuming countries have changed over time with the increasing speed of adjustments since the 1970s.

Table 3 reports the results from the PS relative convergence test. The point estimate of \( \hat{b} \) is largely positive for the whole period, implying that the null hypothesis of convergence is firmly not rejected. The relative transition curves for 1980–2017 in Fig. 2 show fluctuations until the beginning of the 1960s and provide a clear convergence pattern by the mid the 1960s. We proceed with the sub-sample analysis to analyze the impact of transition in oil consumption on the log \( t \)-test.

For the first sub-sample (1980–1929), the point estimate of \( \hat{b} \) is negative but is not significantly different from zero, indicating convergence of oil consumption during this period. The relative transition curves for the 1980–1929 period show that a convergence pattern of the countries (except Japan) was in a narrow band until the 1910s. It then speeded to a broader band. The broader relative convergence patterns after the 1910s are probably because oil discoveries changed the initial conditions. For the second sub-sample (1930–1969), the point estimate of \( \hat{b} \) is largely positive so that the convergence of oil consumption is retained. The relative transition curves for this sub-sample approach to one that provides strong evidence of the ultimate convergence. It is natural to observe this phenomenon as a part of the reconstruction phase following the world war. For the third sub-sample (1970–1993), the point estimate of \( \hat{b} \) is still positive, confirming the validity of convergence. Nonetheless, the point estimate of the convergence parameter decreases to 0.215 in this period from 3.536 in the 1930–1969 period. From 1970 to the 1990s, industrialized countries met their energy needs mainly from fossil fuels. However, dependence on Middle Eastern oil declined due to discoveries. Although renewable energy development gained some track, the lack of feasible alternatives to oil created a technology lock-in leading to relative convergence. We can interpret this result as an indication of transition from convergence to an initial divergence phase. Indeed, the dynamics of relative transition curves for 1970–1993 strengthen this intuition. While relative transition curves appear to be clustered around unity, advanced industrial economies such as the USA, Canada, and the Netherlands keep their higher levels relative to newly industrialized and fast-growing economies such as Spain and Portugal. As a matter of fact, the point estimate of \( \hat{b} \) for the fourth sub-period (1994–2017) turns out to be significantly negative, that the null hypothesis of convergence is rejected in favor of divergence at a 1 percent significance level. In this period, while the relative transition curves of some countries, including the USA, Canada, Netherlands, and Australia, diverge upwards from one, those of Denmark, France, United Kingdom diverge below one. The availability, capacity, and acceptance of renewable energy vary across countries. The divergence in oil consumption in this period is probably due to the different speeds by which countries can substitute renewable energy for fossil fuels.

As outlined in Phillips and Sul (2009, p.1168-1169), the \( \log-t \) regression model not only enables to test for the null hypothesis of convergence but also measures the speed of convergence of \( y_2 \). If \( b \geq 2 \) (i.e., \( \alpha \geq 1 \)) and the common growth component \( \mu_i \) follows a random
walk with drift or a trend stationary process, then large values of $b$ will imply absolute (level) convergence. If $0 < b < 2$, then this speed of convergence corresponds to conditional convergence. Moreover, the higher the value of $b$, the faster the rate of convergence. Accordingly, the convergence of oil consumption is consistent with the absolute convergence for the whole period 1980–2017 and the second sub-period 1930–1969, and with the conditional convergence for the third sub-period 1970–1993, with a faster rate of absolute convergence than that of conditional convergence.

The log-t test implies that the convergence pattern of oil consumption changes over time, and there is a divergence behavior during the last decades. An underlying reason behind this result can be attributed to the common stochastic trend given by $\mu_t$, in model (4), which is dominant in the panel of the largest oil consumer countries. To this end, we plot the sample cross-section averages of oil consumption for the 1994–2017 period in Fig. 4. The common stochastic trend (the sample cross-section averages can capture that) is distinctly decreasing over time. The weak $\sigma$-convergence test of KPS does not include any restriction, and hence it is a useful and flexible way to examine the convergence phenomenon.

Table 4 reports the results from the KPS weak $\sigma$-convergence test. We first consider no common factor ($k = 0$) in oil consumption. Following KPS, we proceed with a factor structure of oil consumption up to three common factors by estimating unobserved common factors with the CCE: Common correlated effects model of Pesaran (2006). The cross-sectional averages of the dependent and explanatory variables were used as the estimated common factors.

The $t$-statistics were estimated with Windmeijer-corrected standard errors for system GMM, and with Newey-West HAC standard errors based on Bartlett kernel with $T^{1/3}$ bandwidth for CCE.

Cross-section dependency tests: $LM$ test of Breusch and Pagan (1980) has chi-square distribution with $N(N-1)/2$ degrees of freedom, $LM_{adj}$ of Pesaran et al. (2008) is the bias-corrected $LM$ test with standard normal distribution, $CD_{adj}$ and $CD$ tests of Pesaran (2021) have standard normal distribution. The tests were based on the OLS residuals from equation (2). The numbers in brackets are the $p$-values of test statistic.

**Note:** $***$, $**$, and $*$ indicate statistical significance at 1, 5, and 10 percent level of significance, respectively.

### Table 2
Results for $\beta$-convergence.

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<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\beta}$</td>
<td>-0.365</td>
<td>-0.187</td>
<td>-0.276</td>
<td>-0.252</td>
<td>-0.320</td>
</tr>
<tr>
<td>$t_{\hat{\beta}}$</td>
<td>-1.150</td>
<td>-0.600</td>
<td>-1.120</td>
<td>-1.130</td>
<td>-1.260</td>
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<tr>
<td>$\gamma$</td>
<td>1.166</td>
<td>0.329</td>
<td>1.748</td>
<td>-0.415</td>
<td>0.274</td>
</tr>
<tr>
<td>$t_\gamma$</td>
<td>0.710</td>
<td>0.550</td>
<td>1.240</td>
<td>-1.44</td>
<td>1.450</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.825</td>
<td>0.851</td>
<td>0.683</td>
<td>0.072*</td>
<td>0.368</td>
</tr>
<tr>
<td>Hansen</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>CCE</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

GMM: Two-step system GMM estimator of Blundell and Bond (1998). The levels of the explanatory variables are used as the instrumental variables. The $p$-value of the Hansen test for validity of the over-identifying restrictions. The $p$-value of the AR(2) test for second order autocorrelation.

CCE: Common correlated effects model of Pesaran (2006). The cross-sectional averages of the dependent and explanatory variables were used as the estimated common factors.

The $t$-statistics were estimated with Windmeijer-corrected standard errors for system GMM, and with Newey-West HAC standard errors based on Bartlett kernel with $T^{1/3}$ bandwidth for CCE.

Cross-section dependency tests: $LM$ test of Breusch and Pagan (1980) has chi-square distribution with $N(N-1)/2$ degrees of freedom, $LM_{adj}$ of Pesaran et al. (2008) is the bias-corrected $LM$ test with standard normal distribution, $CD_{adj}$ and $CD$ tests of Pesaran (2021) have standard normal distribution. The tests were based on the OLS residuals from equation (2). The numbers in brackets are the $p$-values of test statistic.

### Table 3
Results for relative convergence.

<table>
<thead>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{h}$</td>
<td>5.873</td>
<td>-1.951</td>
<td>3.536</td>
<td>0.215</td>
<td>-1.517***</td>
</tr>
<tr>
<td>$t_{\hat{h}}$</td>
<td>13.665</td>
<td>-1.281</td>
<td>25.481</td>
<td>6.828</td>
<td>-51.616</td>
</tr>
</tbody>
</table>

Hodrick and Prescott filtered data with bandwidth 400 was used in the log-t regressions. The $t$-statistics were estimated with Newey-West HAC standard errors based on Bartlett kernel with $T^{1/3}$ bandwidth. $***$, $**$, and $*$ indicate statistical significance at 1, 5, and 10 percent level of significance, respectively.
Table 5 summarizes the results from the $\beta$, relative, and weak $\sigma$-convergence tests. The system GMM results sharply contrast with those from the CCE. This finding indicates the importance of accounting for cross-correlation across the countries to examine $\beta$-convergence. In $\beta$-convergence analysis, the transition parameter is assumed homogeneous across cross-sections, and estimations can critically depend on a set of (omitted or irrelevant) control variables. The relative convergence does not include these pitfalls and can provide insightful information. Apart from the $\beta$-convergence estimations, the relative convergence log-t test supports evidence of the divergence in oil consumption for the 1994–2017 period. Nonetheless, the relative convergence strictly requires a common trend with a distinct non(stochastic) trend in the panel. The notion of weak $\sigma$-convergence does not impose such restriction, and it is meaningful if the notion of relative convergence is not well defined.

Fig. 2. Relative transition curves.
Hodrick and Prescott filtered data with bandwidth 400 was used in the log-t regressions. The t-statistics are estimated with Newey-West HAC standard errors based on Bartlett kernel with $T^{(1/3)}$ bandwidth. ***, **, and * indicate that the null hypothesis of no weak $\sigma$-convergence is rejected at at 1, 5, and 10 percent level of significance, respectively.

For two sub-samples (1890–1929 and 1930–1969), the relative and weak $\sigma$-convergence tests do not appear in agreement that the weak $\sigma$-convergence is more meaningful in such cases. For the 1970–1993 period, the weak $\sigma$-convergence test, in line with the relative convergence test, indicates evidence of the convergence in oil consumption. For the 1994–2017 period, the weak $\sigma$-convergence test, again in line with the relative convergence test, indicates evidence of the divergence in oil consumption. In this situation, rejection of the null hypothesis of relative convergence for the whole panel cannot rule out the existence of club convergence in the panel, and the clustering algorithm in PS can be performed to investigate the possibility of convergent clubs (see Sul, 2019, p.125-126).

PS develop a multiple steps data-driven algorithm to identify the convergent clubs. The first step requires ordering the per capita oil consumption of the countries in the panel based on final observation. Next, starting from the highest-order cross-section, sequentially estimate equation (8) on the $m$ highest cross-section to identify a core group using the cut-off point criterion: $m = \text{ArgMax}_m \{t_{n_m} \}$, subject to $\text{Min}_m \{t_{n_m} \} > -1.65$, for $m = 2, 3, \ldots N$. In the next step, add one cross-section at a time from the remaining cross-section to the core group, and re-estimate log-t regression using the sign criterion ($\hat{b} > 0$) to determine whether to add a cross-section to the core group. These steps are repeated for the remaining cross-section until clubs can no longer be formed.

Table 4 reports the results from the club convergence test for the 1994–2017 period among the largest oil consumer countries. The clustering algorithm classifies the panel into five groups. Evidently, there are four convergent clubs in which the estimated regression coefficients are positive, with the t-ratios larger than $-1.65$. The fifth classification is a non-convergent group (NCG) where the estimated regression coefficient is negative with the t-ratio less than $-1.65$. For the convergent clubs 1 through 4, the point estimates ($\hat{b}$) are positive and less than 2, implying strong evidence of conditional convergence within each group.

It is worth noting that the club convergence method overestimates the number of clubs. The club merging test can be performed to examine whether clubs can be potentially merged (see Phillips and Sul, 2009). Table 6 also reports the test statistics for club merging on the initial

---

Table 4

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>$k = 0$</td>
<td>$\phi -0.018^{**}$</td>
<td>0.0084</td>
<td>$-0.0446^{**}$</td>
<td>$-0.0094^{**}$</td>
<td>0.0033</td>
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<tr>
<td></td>
<td>$t_{\phi} -5.299$</td>
<td>1.198</td>
<td>$-1.789$</td>
<td>$-10.852$</td>
<td>10.536</td>
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<td>$k = 1$</td>
<td>$\phi -0.001^{**}$</td>
<td>0.0015</td>
<td>$-0.0040$</td>
<td>$-0.0003^{***}$</td>
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<tr>
<td></td>
<td>$t_{\phi} -1.995$</td>
<td>1.341</td>
<td>$-0.967$</td>
<td>$-2.613$</td>
<td>11.025</td>
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<tr>
<td>$k = 2$</td>
<td>$\phi -0.0004^{**}$</td>
<td>0.0007</td>
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<td>$t_{\phi} -1.829$</td>
<td>0.920</td>
<td>$-1.277$</td>
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<td>$\phi -0.0003^{**}$</td>
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<td>$-0.0003^{***}$</td>
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<td>$t_{\phi} -2.214$</td>
<td>0.676</td>
<td>$-1.493$</td>
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$k$ is the number of common factor. The t-statistics were estimated with Newey-West HAC standard errors based on Bartlett kernel with $T^{(1/3)}$ bandwidth. ***, **, and * indicate that the null hypothesis of no weak $\sigma$-convergence is rejected at at 1, 5, and 10 percent level of significance, respectively.

Table 5

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<tbody>
<tr>
<td>$\beta$-convergence</td>
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<td>No</td>
<td>No</td>
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<td>Conditional</td>
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</tr>
<tr>
<td>Relative convergence</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Divergence</td>
</tr>
<tr>
<td>Weak $\sigma$-convergence</td>
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<td>Yes</td>
<td>Divergence</td>
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<td>Divergence</td>
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Table 6

<table>
<thead>
<tr>
<th>Results for club convergence (1994–2017).</th>
<th>Club1</th>
<th>Club2</th>
<th>Club3</th>
<th>Club4</th>
<th>NCG</th>
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</thead>
<tbody>
<tr>
<td>$\hat{b}$</td>
<td>0.681</td>
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<td>0.063</td>
<td>0.121</td>
<td>$-1.838^{**}$</td>
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<tr>
<td>$t_{\hat{b}}$</td>
<td>5.303</td>
<td>1.869</td>
<td>0.822</td>
<td>3.727</td>
<td>$44.765$</td>
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<td>Club Merge</td>
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<td>Club2+3</td>
<td>Club3+4</td>
<td>Club4+NCG</td>
<td></td>
</tr>
<tr>
<td>$\bar{b}$</td>
<td>$-0.706^{***}$</td>
<td>$-1.230^{***}$</td>
<td>$-0.490^{***}$</td>
<td>$-1.721^{***}$</td>
<td></td>
</tr>
<tr>
<td>$t_{\bar{b}}$</td>
<td>$-34.673$</td>
<td>$-51.742$</td>
<td>$-37.152$</td>
<td>$63.846$</td>
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<td>Club Members</td>
<td>Australia</td>
<td>Finland</td>
<td>Switzerland</td>
<td>Denmark</td>
<td>Canada</td>
</tr>
<tr>
<td></td>
<td>United States</td>
<td>Norway</td>
<td>Germany</td>
<td>France</td>
<td>Italy</td>
</tr>
<tr>
<td></td>
<td>Spain</td>
<td>Japan</td>
<td>Sweden</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Hodrick and Prescott filtered data with bandwidth 400 was used in the log-t regressions. The t-statistics are estimated with Newey-West HAC standard errors based on Bartlett kernel with $T^{(1/3)}$ bandwidth. ***, **, and * indicate statistical significance at 1, 5, and 10 percent level of significance, respectively.
countries with the highest (above 900 gallons) annual per capita oil consumption in the sample (except for Canada). There is also no distinct pattern in which G7 countries are classified into different clubs. However, the existence of diverse clubs indicates no global convergence. The first club includes countries with the highest (above 900 gallons) annual per capita oil consumption in the sample (except for Canada). The second club is not exhaustively Nordic, probably because Sweden has a large nuclear energy share, the highest carbon tax in Europe, and its own green certificate system. On the other hand, Denmark is a leading innovator in wind energy and is more connected to mainland Europe; hence, not in this club. Although Norway is a global leader in hydropower use, it is a peculiar case since it also is an oil exporter. The third club is difficult to assess, yet high nuclear energy use and electricity exports can be driving this club formation for all except Japan. The countries in the fourth club, Denmark, France, and the UK, have medium carbon taxes (€23.28, €45, and €21.23 per metric ton of CO2e, respectively), which may provide partial explanation to the formation of this club. Finally, each non-convergent club member has more than 40% renewable energy share and is highly dependent on oil imports.

The relative transition paths for each country forming the convergent clubs are plotted in Fig. 3. The transition curves provide relative paths of oil consumption across countries. It is apparent that even though there is heterogeneity across the countries, differences in the relative oil consumption of the club members disappear and converge with each other over time. Fig. 3 further shows the relative transition paths of the clubs. The transition curves indicate clear evidence of divergence across clubs that appear to be accelerated over time. In sum, the relative oil consumption for the 1994–2017 period does not appear to be converging over time; but the countries can form convergent clusters among four different subgroups.

6. Concluding remarks and policy implications

6.1. Conclusion

Using historical oil consumption data for the largest oil consumers over nearly a century and a half (1890–2017), this study examines the convergence properties of oil consumption by distinguishing between weak σ-convergence, relative/club convergence, conditional and absolute convergence. This distinction allows us to increase the policy relevance of our study and provides new insights into the convergence analysis. Since convergence is unlikely to follow a continuous pattern, we split our sample period into different subperiods to capture the role of possible oil shocks and past events in the convergence pattern across countries. Furthermore, we propose an innovative methodology for overcoming the possibility of invalid statistical inferences by accounting for both cross-sectional dependence and the existence of common factors to obtain accurate estimates. We provide a potential analysis mechanism for large oil consumers such as Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States. These countries have high heterogeneity between their regions and degree of dependence on oil consumption.

We find that considering common factors in the dynamics of oil consumption leads to the convergence of oil consumption, regardless of the subperiods. However, we demonstrate that the convergence of oil consumption is conditional over the following subperiods, 1930–1969, 1970–1993, and 1994–2017, while there is evidence of absolute convergence of oil consumption only during 1890–1929. The episode of absolute convergence is mainly observed during the period before the great depression. This is not surprising since oil consumption was under less pressure during this period. Given the evidence of conditional convergence in most cases, one can infer that the convergence pattern of oil consumption tends to be conditional on factors including GDP per capita in each country. This implies that the GDP per capita level should be considered when examining the pattern of convergence of oil consumption. Another key finding is that our study supports the relative convergence of per capita oil consumption among the countries, except for the subperiod 1994–2017. Given the evidence of divergent trend behavior in oil consumption from 1994 to 2017, it is essential to examine whether the variation in oil consumption across countries has significantly decreased via weak σ-convergence. The divergence persists over the last subperiod, 1994–2017. Finally, we also find evidence for...
four convergence clubs. By looking at the dynamics of convergence patterns, we observe that relative transition paths differ across convergence clubs, suggesting that a unified policy may not be tenable. Future research on the determinants of different levels of convergence may shed more light on the phenomenon and help design tailor-made policies for individual countries with different convergence patterns.

6.2. Policy recommendations

Above all, the per capita oil demand should be managed resource-effectively. The divergent pattern observed after 1994 might raise serious concerns about the transition from oil-based energy to renewables. Such transitions require a significant change in the current energy system to reduce countries’ dependence on oil. However, if this divergent pattern among the largest consumers were to continue, it would lead us to a world dominated by an excessive oil consumption pattern across countries with less evidence of a catching-up effect. As a result, the existing energy policy cannot be reliable. Governments across the globe should adopt a new frame of energy policy to reverse the divergent trend in oil demand, which can be summarized as follows. First, countries may improve their energy efficiency by restricting the consumption of high-energy intensive goods and promoting green practices across all sectors. As Bilgili et al. (2021) suggested, this can be achieved by increasing the share of public budgets devoted to research and development in the renewable energy sector. Secondly, policymakers may identify oil-intensive sectors and build a proper framework and mechanism for regular energy audits to reduce their dependence on conventional energy sources. The underlying countries in our study can ensure a sustainable convergence pattern only when the expansion of oil demand is complemented with policies toward improving oil efficiency. Finally, given the role of GDP per capita in realizing the convergence pattern, policymakers may continue to improve the degree of decoupling between GDP per capita and oil consumption per capita. According to the European Environment Agency (2018b), efforts for a successful decoupling should be driven by structural change towards services and greener industries and efficiency improvements in all sectors.

CRediT authorship contribution statement

Saban Nazlioglu: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision. Yacouba Kassouri: Conceptualization, Methodology,


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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Supplementary csv file

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.113150.

References


