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Estimating Persistent and Transient Energy Efficiency in Belt and Road Countries: A Stochastic Frontier Analysis

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Abstract: In this paper, we examine the energy efficiency performance of the Belt and Road Initiative (BRI) countries using a newly developed panel data stochastic frontier model that allows for estimation of both persistent and transient efficiency while controlling for random country effects and noise. By this, we contribute to the energy economic literature by providing a complete picture of the level of persistent, transient, and total energy efficiency estimates from a cross country perspective for a panel of 48 BRI countries during the period 1990–2015. Adding that there is little evidence to support energy efficiency convergence in the energy economic literature, we went further to check whether energy efficiency converges in the BRI countries. The results show that (1) persistent efficiencies are much lower than transient efficiencies, suggesting that the energy problem in the BRI countries is more of a structural issue; (2) while energy efficiency varies widely across the countries, high-income countries perform better than the lower-income countries; (3) there is evidence of efficiency convergence and it accelerates when trade increases, but decreases when the industrial sector increases. Based on these findings, we propose some policy implications.

Keywords: BRI; energy efficiency; transient efficiency; persistent efficiency; efficiency convergence

1. Introduction

In 2013, the Chinese President, Xi Jinping launched the Belt and Road Initiative (BRI) to stimulate and foster economic growth in neighboring European, Asian, and African countries. So far, this initiative encompasses 65 countries (most of which are developing economies), representing about 60% (i.e., 4.4 billion) of the global population. The BRI is expected to drive a new round of global economic boom in countries along the BRI region [1], but there are concerns from experts and the international community about the potential environmental consequences concerning energy use (https://knowledge.wharton.upenn.edu/article/can-chinas-one-belt-one-road-initiative-match-the-hype/). Therefore, one of the key focuses of the BRI is to improve energy supply, energy efficiency, and supply clean energy within the region [2]. Specific policies to encourage energy efficiency have also been introduced at the country level [3]. To ensure the success of these programs and to take full advantage of these regional and national measures, a deeper understanding of energy efficiency assessment is essential to set the right targets to attain the energy efficiency objectives.

In light of this, a major area of research has recently focused on assessing energy efficiency performance within the BRI region [4–7]. However, these researchers have failed to distinguish

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between transient and persistent energy efficiency. According to the energy economic literature, energy inefficiency is composed of two parts, one persistent and the other transient. The persistent part has to do with the presence of structural issues in the production process, poor managerial skills, and infrastructural bottleneck [8,9]. It may also be linked to systematic behavioral failures like failing to replace outdated machineries for a long period. Thus, the persistent energy inefficiency captures long-run inefficiency, which does not vary over time, unless there are some major changes in energy policies [10,11]. On the other hand, transient inefficiency may emanate from unsystematic management problems like the poor selection of suppliers, suboptimal resource allocation, trial-and-error processes in unknown circumstances, and delays in the replacement of obsolete and inefficient equipment and tools. Transient energy inefficiency therefore captures short-run inefficiency, which varies over time and can be addressed in the short term [11].

Differentiating between the two types of efficiency will help policymakers under the BRI decide in an informed way on what energy policy tools to adopt to increase efficiencies. Thus, for transient inefficiency, energy policies that bring about short-term behavioral changes in energy consumption can be given more attention. Likewise, energy policy measures aimed at encouraging innovation and technology spillover can be considered in the long-term to reduce persistent inefficiency.

Although energy efficiency is an important topic to study, the issue of energy convergence in the cross-country perspective has largely been ignored. Notable exceptions are Adom et al. [8], Stern [12], and Liddle and Sadorsky [13]. According to Qi et al. [6], in the last 20 years, the BRI countries have contributed nearly 30% to the world's GDP using almost a 50% share of global energy, which suggests that energy efficiency performance in several of BRI countries is low [6,14,15]. Based on this background, we must check whether efficiency performance in these inefficient countries are generally catching up or still falling behind to the initially higher efficient ones. Investigating whether the BRI countries narrow their efficiency gap has potential implications for negotiating international climate change agreements and fulfilling national and regional targets on energy security, energy efficiency, and CO₂ emission reductions [13]. Thus, in addition to energy efficiency estimation, we examined whether countries with poor energy efficiency converges or diverges and factors that may induce the rate of convergence or divergence.

Driven by the above, the following are the main contents of this paper:

- (1) The energy efficiency performance of 48 BRI countries was first established by employing a stochastic frontier analysis (SFA), where we measured persistent and transient efficiency. Through this, the paper contributes to the energy economic literature by providing a complete picture of the level of persistent, transient, and total energy efficiency estimates for the BRI countries using a recently developed model (by Kumbhakar, Lien, and Hardaker [16]), which is suitable for separating unobserved country-specific heterogeneity from transient and persistent energy efficiency. The inability to control for unobserved country-specific heterogeneities when they exist can bias the estimate of the persistent and transient component, and hence the overall energy efficiency results.
- (2) Second, we checked whether BRI countries with poor energy efficiency are generally catching up (or falling behind) to the initially higher energy efficient ones. Attaining convergence in energy efficiency improvements has vital implications on environmental and sustainable growth for the BRI region. To achieve this aim, we applied the beta convergence on the estimated total energy efficiency index.

The remainder of this paper is arranged as follows. The empirical literature is reviewed in Section 2. The methodology and data used for estimations are discussed in Section 3. In Section 4, the results and findings are discussed. The paper concludes with Section 5 with some highlights of the findings and some policy implications.

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2. Literature Review

2.1. Energy Efficiency

The most cost-effective way to reduce greenhouse gas emissions is to increase energy efficiency [17, 18]. Therefore, over the years, there have been a vast number of studies on energy efficiency estimation using a variety of indicators such as thermodynamic indicator, economic indicator, etc. [19]. From an economic perspective, energy efficiency estimation techniques can be classified under two main groups, namely the total factor energy efficiency (TFEE) and the single factor energy efficiency (SFEE).

The SFEE, which is also called energy intensity, is measured by comparing the economic performance of a country to its energy use. This method is simple and frequently used in the energy economic literature [20–22], but it has a number of issues. For instance, the estimation relies on only one key input that is, energy consumption and abandon other key inputs such as capital and labor in the production function [23]. Additionally, it does not indicate how much energy an individual unit can save. Rather, it simply indicates how high or low the energy consumption of a country is compared to others.

The total factor energy efficiency (TFEE) on the other hand, considers all key production inputs like labor, capital, and energy simultaneously in the efficiency estimation [7,24–28]. Using TFEE requires estimating the frontier in a fashion that follows either the stochastic frontier analysis (SFA) or the data envelopment analysis (DEA). The DEA, a non-parametric estimation technique, built on a mathematical programming was proposed by Boles [29] and Afriat [30]. Ever since it was proposed, it has been used widely in estimating energy efficiency. To name a few, Mukherjee [31] estimated energy efficiency levels of the United States manufacturing sector using the DEA. Mukherjee [32] measured the efficiency of Indian manufacturing firms using the DEA. Jebali et al. [23] examined the energy efficiency performance of Mediterranean countries between 2009 and 2012. Gökgöz and Erkul [33] compared the efficiency levels of European countries during the period of 2011–2015 using DEA.

The DEA imposes no functional form and distributional assumptions on the model and therefore it is free from model specification, but this makes the DEA exposed to omission variable bias and measurement problem. Most importantly, the DEA considers the stochastic noise as part of the inefficient factors, which may bias the estimated efficiencies. Therefore, in the current study, we adopted the SFA because we considered the stochastic noise relevant to be controlled in our estimation.

The SFA, proposed by Aigner et al. [34] and Meeusen et al. [35] imposes a functional form and distributional assumptions, making the model robust to omission variable bias and measurement errors. Generally, studies employing SFA to estimate energy efficiency use either an aggregate production function [7,36] or aggregate demand function [37,38]. The aggregate demand approach has the benefit of including energy prices, which, according to economic theory, has a significant influence on the efficiency of energy services. However, the addition of energy prices to the model, often limits studies to Organization for Economic Co-operation and Development (OECD) countries [13]. In this study, we made an effort to consider non-OECD countries.

Filippini and Hunt [39] proposed the aggregate energy demand and had it tested in 29 OECD countries. In the model, the authors controlled for income, price of fuel, climatic conditions, area, industrial structure, service industry, and an underlying energy demand trend to estimate energy efficiency. The results showed that variables such as income, country area, population, industrial structure, service structure, and the climatic conditions had a positive and significant effect on energy use. However, energy prices had a negative impact on energy use. In their conclusion, they stressed that energy intensity is a bad energy efficiency proxy. Filippini and Hunt [40] estimated the residential energy demand of 48 U.S. states and showed a positive and significant relationship between energy consumption and variables such as income, population, average household size, heating degree days, cooling degree days, and share of detached houses. Again, energy prices had a negative impact on energy consumption. Filippini et al. [41] investigated the impact of energy efficiency policies on the European Union residential sector and observed a considerable variation in energy efficiency

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between the EU member states. Furthermore, their results suggest that financial incentives and energy performance standards play an important role in promoting energy efficiency. Marin and Palma [38] measured the aggregate electricity consumption of the European economy. By accounting for potential endogeneity in innovation processes and economic growth, their results showed that the efficiency component is related to changes in the energy efficient technological content of appliances. Song and Yu [42] examined the Chinese provincial energy efficiency levels between 1995 and 2014. While they observed that the provincial energy efficiency during the sample period had improved, provincial energy efficiency seems to have widened. They also noticed that investments and the development of market mechanisms improved energy efficiency. Like, Filippini and Hunt [39,40], they concluded that the energy intensity variable is not a good proxy for energy efficiency.

Some studies make a distinction between transient and persistent efficiency using the energy demand function. For instance, Filippini and Hunt [40] measured the energy efficiency performance of the U.S. economy throughout 1995–2009 using the Mundlak random effects model and the true random effects model. They observed that addressing persistent inefficiency reduced energy consumption by 14% whereas eliminating transient inefficiencies would cut the energy used by 4%. Filippini and Zhang [43] estimated the persistent and transient energy efficiencies of Chinese provinces and their empirical analysis showed that China's average value of persistent energy efficiency was 81%, whereas that of the transient energy efficiency was 97%. Thus, they concluded that China could save 3.3% and 19% of its energy by completely cutting transient inefficiencies and reducing persistent inefficiencies, respectively. Zhang [44] also assessed China's energy efficiency performance and observed that China could save 21.9% of energy if persistent inefficiency was reduced and 3.9% if transient inefficiency was eliminated. Alberini and Filippini [9] measured the residential energy consumption level of the U.S. households' from 1997 to 2009 and observed that the U.S. economy could reduce its energy intensity by 10% if persistent inefficiencies were eliminated. On the other hand, 17% of energy efficiency could also be saved if transient inefficiencies were eliminated.

All the above studies on persistent and transient energy efficiency were from a single country perspective. The only study with a cross country evidence is by Adom et al. [8], who estimated Africa's persistent and transient energy efficiency levels using the model proposed by Kumbhakar and Heshmati [45] (hereafter, the K–H model). Their result shows that Africans can save about 5.7% of energy if transient energy inefficiency is eliminated, while decreasing persistent inefficiency can save 84% of the total energy. Though the K–H model attempts to separate the persistent and transient inefficiency, it fails to control for unobservable country heterogeneity. Thus, this model seems to confound unobservable country effects as part of the inefficiency when in fact, we must treat for unobservable country effects in such model.

To address this, Tsionas and Kumbhakar [46], Kumbhakar et al. [16], Colombi et al. [47], and Filippini and Greene [48] suggest a model that divides the error term into four parts (i.e., persistent inefficiency, transient inefficiency, random country-effects, and noise). Therefore, as opposed to Adom et al. [8], we adopted the Kumbhakar, Lien, and Hardaker [16] model (hereafter, the K–L–H model), which distinguishes between persistent and transient inefficiencies and time invariant inefficiencies from country effects. In view of this, we contribute to the energy economic literature by using a more recent model that estimates both persistent and transient energy efficiency for a panel of 48 BRI countries.

2.2. Energy Efficiency Convergence

Recently, great emphasis has been placed on achieving a fair growth of "Sustainable Energy for all" by 2030 (https://www.seforall.org/who-we-are). Therefore, the convergence hypothesis that was initially used to explain the substantial heterogeneity in economic growth among countries has renewed its status lately in the energy economic literature. While lately there have been some studies on this subject in the energy economic literature, most of them only focus on whether energy efficiency converges or diverges rather than what speeds up the convergence or divergence process [49–51]. In

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this study, while we explore the issue of convergence, we also examined factors that could speed up or decelerate the convergence in energy efficiency.

Energy efficiency convergence, in particular within a developing economy, is closely linked to industrial structure, the level of economic development, FDI, trade, and technology [52,53]. For African countries, Adom et al. [8] concluded that energy efficiency convergence is conditional on FDI and the industrial structure. Han et al. [54] concluded that energy efficiency convergence for BRI countries depends on trade and regional collaboration. Considering that the energy efficiency performance of several BRI countries is low, it is worth investigating whether efficiency converges or diverges in these countries. Furthermore, the increased trade and investments between China and the BRI countries make further investigations worthy of the effect of trade and FDI on energy efficiency convergence [6]. Thus, in this paper, we examined the influence of trade and FDI on energy efficiency convergence across the BRI countries.

3. Methodology

3.1. Stochastic Energy Demand Function

We adopted the concept of input demand frontier explained in Kumbhakar et al. [55] to illustrate the energy demand. Thus, our modeling is based on production theory where we relate energy demand in a country to its economic activities and the actual price of energy (According to the standard production theory, the input demand for energy is considered a derived demand). In this context, the efficient use of energy means producing a particular level of output with minimum input. To estimate energy efficiency, we followed Filippini and Hunt [39], who formulated an energy demand frontier and carried out the energy efficiency estimation. Energy efficiency is the estimation of the difference between actual energy usage and optimal energy demand, as determined by an estimated demand frontier. Thus, the specification of the stochastic frontier approach, according to the energy demand frontier is as follows:

$$ED_t^c = \beta_0 + x_t^c \beta + \varepsilon_t^c \tag{1}$$

where the dependent variable ED_t^c is the aggregate energy demand in country (c) at time (t) and x_t^c represents the vector of inputs that influences the demand for energy services: price of fuel (P), gross domestic product (GDP), population density (PD), share of value from the service sector (SS), the share of value from the industry (IS), and underlying energy demand trend (UEDT). In Filippini et al. [41], the UEDT captures the effect of technical progress on energy consumption, following suit, we included a time trend to represent UEDT. β is the vector of parameters to be computed. ε_t^c is a two-error component consisting of two terms, namely the noise term and the inefficiency term.

As already mentioned, we differentiated between persistent and transient efficiency using the multistep approach proposed by Kumbhakar, Lien and Hardaker [16]. While there are other models (e.g., Tsionas and Kumbhakar [46], Colombi et al. [47], and Filippini and Greene [48]) that estimate both persistent and transient efficiency, the K–L–H model proposed by Kumbhakar, Lien and Hardaker [16] has the advantage of avoiding strong distributional assumptions by estimating the model using the maximum likelihood approach. To estimate the K–L–H model, we rewrote Equation (1) as:

$$ED_t^c = \beta_0^* + x_t^c \beta + u_c + \varepsilon_t^c$$
 (2)

where
$$\beta_0^* = \beta_0 - E(\eta_c) - E(u_t^c)$$
, $u_c = \gamma - \eta_c - E(\eta_c)$, and $\varepsilon_t^c = v_t^c - u_t^c + E(u_t^c)$

In this specification, u_c and ε_t^c have zero mean and constant variance. With Equation (2), we used the 4-step approach to estimate the K–L–H model. In the first step, the standard fixed-effect panel regression was used to estimate $\hat{\beta}$. This technique also gives the values of u_c and ε_t^c denoted by \hat{u}_c and $\hat{\varepsilon}_t^c$. In step 2, we used the predicted value of $\hat{\varepsilon}_t^c$ from the previous step to estimate the time-varying efficiency u_t^c using the standard stochastic frontier technique. Here, we assumed that v_t^c is a random noise i.i.d $N(0,\sigma_v^2)$ and u_t^c is $N^+(0,\sigma_u^2)$. To this end, this procedure predicts the time-varying residual

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energy efficiency using the Battese and Coelli [56] procedure, $TEE_t^c = exp(-u_t^c|\varepsilon_t^c)$. In step 3, we estimated persistent energy efficiency η_c following a similar procedure as in step 2. For this, we adopted the standard pooled half-normal stochastic frontier model to obtain estimates of the persistent efficiency component η_c . Again, persistent energy efficiency (PEE) can be estimated using the Battese and Coelli [56] procedure i.e. $PEE_t^c = exp(-\hat{\eta}_c)$. Finally, the total energy efficiency (OTE) is extracted as the product of the persistent energy efficiency and transient energy efficiency, that is $OTE_t^c = PEE_t^c \times TEE_t^c$, where the total energy efficiency index (OTE) is equal to one if the country is on the frontier and therefore considered to be energy efficient, while an index less than one is below the frontier and is energy inefficient.

3.2. Other Models for Robustness

While the K–L–H model has the potential to estimate persistent and transient efficiency simultaneously, there are other models that either estimate only persistent or transient efficiency.

For example, the fixed effect model (FEM) assumes that the efficiency term does not vary over time, but varies across countries, therefore, it estimates the persistent component of efficiency. Unlike the FEM, which is fitted by ordinary least squares (OLS), the Greene true fixed effect model (GTFEM) proposed by Greene [57,58] is fitted by maximum likelihood and it separates country-specific effects from the inefficiency and allows the inefficient component to vary over time. Thus, the GTFEM only estimates the transient component of efficiency. However, the GTFEM sometimes suffer from an incidental parameter problem and produces an inconsistent estimation of the parameter variance [59]. Chen et al. [59] proposed the consistent true fixed effects model (CTFEM) to address the incidental parameter problem. For robustness of results of the K–L–H model, in this paper, we applied the FEM, CTFEM as well the K–H model adopted by Adom et al. [8] to compute the persistent and transient efficiency and overall energy efficiency.

3.3. Energy Efficiency Convergence

Aside from estimating efficiency, we also investigated the efficiency convergence by means of the β -convergence. The β -convergence means that less energy efficient countries tend to grow quickly as they try to catch up to the efficient ones. According to the convergence hypothesis, the unconditional β -convergence specification is stated as in Equation (3):

$$\ln\left(\frac{OTE_{c}^{t}}{OTE_{c, t-1}}\right) = \alpha + \beta \ln OTE_{c, t-1} + \varepsilon_{c}^{t}$$
(3)

where OTE_c^t denotes the energy efficiency of country (c) at year (t). α is the constant term; $OTE_{c,\ t-1}$ is the reciprocal value of first-order lagged energy efficiency; and β represents the speed of convergence. A negative β , which is significantly different from zero, means that β -convergence is confirmed. ϵ_c^t is the stochastic error term.

As stated earlier, we examined the role of FDI and trade on energy efficiency convergence. FDI is a crucial channel for energy efficient technologies and innovations to be transferred from one country to another. Thus, we expect that the inflow of FDI should increase energy efficiency convergence. Trade improves efficiency when better technologies are imported and used in production. Importing a wide range of high–tech machinery and equipment will contribute enormously to improving efficiency. We therefore envisage the net effect of trade on energy efficiency convergence to be positive.

In addition to FDI and trade, we controlled for the industrial structure in the model. The industrial structure is also one of the major factors that determine the energy intensity level of a country [60,61]. The BRI countries (which are mainly developing economies) are more dependent on secondary industries that are energy intensive than developed countries, whose tertiary industries are highly developed. Thus, we expect the industrial structure to have a negative effect on energy efficiency

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convergence. We also controlled for unobserved country effects within the model by adding the fixed effect term (μ_c) in Equation (4), Thus, we have:

$$ln\left(\frac{OTE_{c}^{t}}{OTE_{c, t-1}}\right) = \alpha + \beta lnOTE_{c, t-1} + \gamma FDI_{c}^{t} + \gamma Trade_{c}^{t} + Indus_{c}^{t} + \mu_{c} + \epsilon_{c}^{t}$$
(4)

3.4. Variables and Their Sources

In this paper, we initially considered all 65 BRI countries, however, due to data unavailability, we limited ourselves to a sample of an unbalanced panel dataset of 48 countries for the period of 1990 to 2015 (see Table A1 in Appendix A for the list of countries). The energy price index data are also not available for the sample countries, so we used the real crude oil price as a proxy for energy price and assumed that the price of energy is different for years, but not across different countries [8]. In other words, we assumed that the BRI countries are influenced by a common crude oil energy trend. We used a total of ten variables. Table 1 defines all variables and their sources, while Table 2 shows the descriptive statistics of all variables.

Table 1. Variables, definitions, and sources.

Variables	Symbols	Definition	Source
Energy Demand	lnED	The natural logarithm of energy use	WDI
Fuel price	lnPrice	The natural logarithm of real crude oil price measured in US\$/barrel	BPE
Gross Domestic Product	lnGDP	The natural log of GDP measured in constant US dollar.	WDI
Population density	lnPD	The natural logarithm of population density computed as people per sq. km of land area	WDI
Share of value from the Industry	Service	Value added by industry measured as share of gross domestic product	WDI
Share of value from the Service sector	Indus	Value added by services measured as share of gross domestic product	WDI
Per capita income	lnincome	The natural log of per capita income measured in constant US dollar.	WDI
Trade	Trade	The sum of exports and imports measured as a share of gross domestic product.	WDI
Foreign Direct Investment	FDI	Net inflows measures as percentage of GDP	WDI
Underlying Energy Demand Trend	Trend	Underlying Energy Demand Trend (UEDT).	
Energy Efficiency Index	EE	Total Energy Efficiency Index extracted from the K–H model	

Note: BPE: BP Statistical Review of World Energy; WDI: World Development Indicator. Source: Authors' compilation.

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Variable	Obs	Mean	S.D.	Min	Max
lnED	1248	7.28	0.98	4.75	9.40
InPrice	1248	3.91	0.56	2.95	4.80
lnGDP	1209	24.45	1.74	20.30	30.03
lnPD	1248	4.41	1.30	0.34	8.96
Service	1241	48.80	10.74	11.35	95.80
Indus	1187	32.14	11.44	9.37	74.61
lnIncome	1207	7.976	1.395	4.553	10.950
FDI	1145	4.328	8.358	-43.463	198.074
Trade	1197	93.928	54.916	15.675	441.604

Table 2. Descriptive summary statistics.

Source: Authors' compilation.

4. Empirical Results and Discussion

4.1. Results for the Energy Demand Function

Table 3 presents the results for the energy demand frontier function using the FEM and CTFEM. The choice of the fixed effect model is informed by the Hausman test, which rejects the random effect model (see Table A2 in Appendix A for the results). As some variables are in log–log form, their coefficients can be interpreted as elasticity. Starting with energy price, it has a significant and negative effect on energy demand. In both models, the price elasticity is negative and very low. On average, a percentage increase in fuel price will result in a decrease of about approximately 0.067% in energy consumption, all else being equal. Filippini and Hunt [10,39] also found similar results for the U.S. and OECD economies, respectively.

On the other hand, the variable for income is positive and significant in both models. On average, a 1% growth in GDP will increase energy demand by 0.33%. The income elasticity of energy demand is, as expected, relatively high in the BRI countries, since they are predominantly emerging economies. Similar results were found in Filippini and Zhang [43] for China and Adom et al. [8] for Africa. However, this is in contrast to those found for OECD countries in Marin and Palma [38].

As for population density, the estimated coefficient is negative and statistically significant in the models, suggesting that a percentage increase in population will lead to a decrease of 0.13–0.15% in energy consumption. To reduce commuting time, there is the tendency for highly-populated areas to switch to the use of the less-energy intensive mode of transportation (e.g., motorcycles) and non-energy way of transportation (e.g., bicycles and trekking). This is typical in highly populated countries like China and India. This result reflects previous studies who found that an increase in population increased the energy efficiency [8,10,62].

As expected, the value added by the service sector had a negative effect on the demand for energy and it was significantly different from zero. Thus, a 1%-point increase in the service sector will reduce energy consumption by 0.008%. This suggests that a shift to a less energy intensive area like the service sector reduces energy use. Similar results were found in Adom et al. [8]. The value added by the industrial sector on the other hand appears to have a positive, but has a statistically insignificant impact on energy demand. The impact of time trend on energy consumption is negative and statistically significant. By insinuation, a negative time trend, combined with a negative price elasticity, indicates that energy-saving technology would be adopted over time and the demand for energy would drop in the BRI countries [10].

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Table 3. Energy demand frontier function results.

Model	(1)	(2)
Independent Variables	Fixed Effect Model	Consistent True Fixed Effect Model
InPrice	-0.0685 ***	-0.0667 ***
	(0.0172)	(0.0171)
InGDP	0.323 ***	0.337 ***
	(0.0194)	(0.0208)
lnPD	-0.150 ***	-0.131 ***
	(0.0463)	(0.0484)
Service	-0.00879 ***	-0.00914 ***
	(0.001)	(0.00121)
Indus	0.00212	0.00190
	(0.0015)	(0.00147)
Trend	-0.009 ***	-0.0107 ***
	(0.0019)	(0.00208)
Constant	0.791 *	
	(0.471)	
sigma_u	0.9499	
sigma_e	0.1669	
Usigma Constant		
Vsigma Constant		
Sigma2 Constant		0.0404 ***
		(0.005)
Lambda		0.9881 ***
		(0.252)
Observations	1185	1185
Cross-section	48	48

Standard errors in parentheses: *** p < 0.01, * p < 0.1. Source: Authors' Compilation.

4.2. Energy Efficiency Analysis

After the energy demand frontier function, we went ahead to compute the persistent, transient, and overall average energy efficiencies based on the four models. In Table 4, we present the descriptive statistics of the transient, persistent, and overall average energy efficiency from these models. As expected, the mean value of transient efficiency was much higher than the persistent efficiency [10]. The mean persistent energy efficiency for FEM is the same as those produced by the K-H model (0.204). In contrast, the mean persistent efficiency of the K-L-H model was 0.465, twice as high as the averages for the FEM and K-H models. The reason for this disparity has to do with the fact that the K-L-H model separate unobserved persistent country effects from inefficiencies that can be confounded in persistent inefficiencies. Thus, the models such as FEM and K-H model that fails to control for unobserved persistent country heterogeneity tend to over-estimate inefficiency scores, hence generating lower estimates of persistent efficiencies. The mean persistent efficiency for BRI countries was higher than those estimated by Adom et al. [8] for African countries (16%), but it is much lower than those estimated by Filippini and Hunt [10] for the U.S. (86%). Given that high persistent inefficiency is attributed to the use of inefficient technology, a low persistent efficiency of 47% implies that it will take time and resources for BRI countries to increase persistent efficiency. It is in this regard that some of the energy infrastructure and policy reforms envisaged in the BRI may address the long-term energy technology problem of the region.

The mean transient technical efficiencies obtained from the CTFEM were 0.895, while both K–H and K–L–H models produced the same values (i.e., 0.934). Thus, average transient energy efficiency

for the K–H and K–L–H models appears to be higher than those of CTFEM, suggesting that there is a downward bias in CTFEM. Nevertheless, the difference is not that significant. A high transient energy efficiency score of 93% suggests that BRI countries, on average, gradually progress toward the benchmark technology in the short term.

Table 4. Summary statistics of persistent, transient, and overall energy efficient	nt, transient, and overall energy efficiency.	Table 4. Summary statistics of persister
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Variable	Obs.	Mean	S. D	Min	Max
Persistent efficiency					
FEM	1185	0.204	0.193	0.019	1
K-H Model	1185	0.204	0.193	0.019	1
K-L-H Model	1185	0.465	0.195	0.112	0.802
Transient efficiency					
CTFEM	1185	0.895	0.038	0.626	0.978
K-H Model	1185	0.934	0.016	0.806	0.974
K-L-H Model	1185	0.934	0.016	0.806	0.974
Total efficiency					
FEM×CTFEM	1185	0.183	0.174	0.016	0.942
K-H Model	1185	0.191	0.181	0.018	0.955
K-L-H Model	1185	0.434	0.182	0.101	0.765

Note: EM, K–H, and K–L–H models estimate persistent efficiency. The CTFEM, K–H, and K–L–H models estimate transient efficiency. Total efficiency is estimated by the K–H model, and the K–L–H model for the interaction terms for FEM and CTFEM.

Despite the high transient energy efficiency recorded in the BRI countries, the average total energy efficiency for the region remains low due to the low persistent efficiency. The results imply that for most countries, persistent energy efficiency has a priority for policy consideration compared to transient energy efficiency since persistent efficiency contributes largely to the low total efficiency. The mean total energy efficiency obtained from the FEM×CTFEM (i.e. the product of FEM and CTFEM), K–H, and K–L–H models was 0.18, 0.19, and 0.43, respectively. As mentioned earlier, the persistent inefficiency scores in the FEM and K–H model tend to be over-estimated due to the failure to control for unobserved country heterogeneity. Thus, the persistent efficiencies score obtained in the FEM and K–H model tends to be lower than those in the K–L–H model. Considering that the true measure of efficiency may be presented by the K–L–H model, our conclusions are therefore based on the K–L–H model. This means that the BRI countries can save around 67 per cent of total energy by improving both persistent and transient efficiency.

Next, we grouped the BRI countries into six regions, and Table 5 shows the summary statistics of the efficiency levels of each region. For persistent efficiency, the Central and Eastern Europe led with a score of 54%, closely followed by Central Asia with 52%. The rest including the Middle East and Africa, South Asia, Southeast Asia, and Northeast Asia had a score of 47%, 44%, 36%, and 34% with an energy saving potential of 53%, 54%, 54%, and 56%, respectively. For the transient efficiency, on average, all regions had a high score and energy saving ability of about 0.1% when transient energy inefficiency was completely reduced.

Generally, Central and Eastern Europe performed better than other regions. This is expected, as countries in this region are mostly developed with improved industrialization and technology. In a similar study, Qi et al. [6] observed that the energy efficiency level for Central and Eastern Europe was greater than for other regions, which is in line with the outcome here. However, regions such as the Middle East and Africa, South Asia, Southeast Asia, and Northeast Asia with relatively low economic growth and poor energy infrastructure have lower energy efficiency scores. This suggests a potential link between the level of development and efficiency performance.

Table 5. Energy efficiency score from a regional perspective.

Regions	Persistent Energy Efficiency			Transient Energy Efficiency			Total Energy Efficiency		
	FEM	К-Н	K-L-H	CTFEM	K-H	K-L-H	FEM*CTFEM	К-Н	K-L-H
Central & Eastern Europe	0.251	0.251	0.577	0.897	0.935	0.935	0.225	0.234	0.540
Central Asia	0.233	0.233	0.554	0.895	0.935	0.935	0.209	0.218	0.518
Middle East & Africa	0.198	0.198	0.499	0.893	0.934	0.934	0.177	0.185	0.465
South Asia	0.184	0.184	0.475	0.894	0.933	0.933	0.165	0.172	0.443
Southeast Asia	0.141	0.141	0.389	0.895	0.934	0.934	0.126	0.132	0.363
Northeast Asia	0.189	0.189	0.365	0.896	0.935	0.935	0.169	0.177	0.341

 $Source: Authors' \ compilation.$

To further study the efficiency in these regions, we examined the changes in energy efficiency in each country. Table 6 shows the energy efficiency score for each country. Given that the true measure of energy efficiency is provided by the K–L–H model, our discussion on changes in energy efficiency in each country is based on the results of this model.

Table 6. Average energy efficiency performance of each country.

Countries	Persistent Energy Efficiency			ient Ene		Total Energy Efficiency			
	FEM	К-Н	K-L-H	CTFEM	К-Н	K-L-H	FEM*CTFEM	К-Н	K-L-H
Brunei Darussalam	1.000	1.000	0.802	0.897	0.935	0.935	0.897	0.935	0.750
Singapore	0.757	0.757	0.776	0.897	0.935	0.935	0.679	0.708	0.726
United Arab Emirates	0.562	0.562	0.743	0.885	0.932	0.932	0.498	0.524	0.692
Estonia	0.550	0.550	0.740	0.909	0.939	0.939	0.500	0.516	0.695
Slovenia	0.390	0.390	0.691	0.911	0.933	0.933	0.355	0.364	0.645
Cyprus	0.359	0.359	0.677	0.900	0.936	0.936	0.323	0.336	0.634
Czech Republic	0.334	0.334	0.665	0.897	0.935	0.935	0.300	0.312	0.622
Slovak Republic	0.322	0.322	0.658	0.888	0.938	0.937	0.286	0.302	0.617
Lithuania	0.304	0.304	0.648	0.903	0.938	0.938	0.274	0.285	0.608
Oman	0.301	0.301	0.646	0.894	0.934	0.934	0.269	0.281	0.604
Bulgaria	0.294	0.294	0.642	0.898	0.935	0.935	0.264	0.275	0.600
Latvia	0.268	0.268	0.624	0.904	0.937	0.937	0.243	0.251	0.584
Belarus	0.267	0.267	0.623	0.898	0.935	0.935	0.240	0.250	0.583
Israel	0.264	0.264	0.620	0.900	0.935	0.934	0.237	0.246	0.579
Lebanon	0.245	0.245	0.605	0.899	0.935	0.935	0.220	0.229	0.566
Moldova	0.234	0.234	0.595	0.893	0.938	0.938	0.209	0.219	0.558
Ukraine	0.225	0.225	0.587	0.898	0.935	0.935	0.202	0.211	0.549
Hungary	0.215	0.215	0.577	0.901	0.938	0.938	0.194	0.201	0.541
Kazakhstan	0.214	0.214	0.576	0.896	0.936	0.936	0.192	0.201	0.539
Croatia	0.214	0.214	0.576	0.909	0.933	0.933	0.194	0.200	0.537
Bosnia and Herzegovina	0.196	0.196	0.555	0.859	0.913	0.912	0.166	0.179	0.507
Azerbaijan	0.195	0.195	0.554	0.863	0.922	0.922	0.168	0.180	0.511
Saudi Arabia	0.178	0.178	0.533	0.898	0.935	0.935	0.159	0.166	0.498
Georgia	0.157	0.157	0.502	0.881	0.932	0.932	0.138	0.146	0.468
Jordan	0.152	0.152	0.495	0.898	0.935	0.935	0.137	0.142	0.463
Mongolia	0.152	0.152	0.494	0.898	0.935	0.935	0.136	0.142	0.462
Poland	0.147	0.147	0.486	0.897	0.938	0.938	0.132	0.138	0.455
Romania	0.142	0.142	0.478	0.893	0.934	0.934	0.127	0.133	0.446
Malaysia	0.135	0.135	0.466	0.893	0.934	0.934	0.121	0.126	0.435
Russia	0.130	0.130	0.455	0.898	0.936	0.936	0.117	0.122	0.426
Albania	0.113	0.113	0.420	0.895	0.934	0.934	0.101	0.106	0.392
Iran	0.112	0.112	0.417	0.900	0.932	0.932	0.101	0.104	0.389

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Table 6. Cont.

Countries	Persistent Energy Efficiency		Transient Energy Efficiency			Total Energy Efficiency			
	FEM	К-Н	K-L-H	CTFEM	K-H	K-L-H	FEM*CTFEM	К-Н	K-L-H
Kyrgyz Republic	0.111	0.111	0.416	0.890	0.933	0.933	0.099	0.104	0.388
Thailand	0.083	0.083	0.343	0.886	0.932	0.932	0.073	0.077	0.320
Tajikistan	0.075	0.075	0.321	0.884	0.930	0.930	0.066	0.070	0.299
Sri Lanka	0.061	0.061	0.277	0.897	0.935	0.935	0.055	0.057	0.259
Turkey	0.061	0.061	0.275	0.899	0.936	0.936	0.055	0.057	0.258
Nepal	0.061	0.061	0.275	0.899	0.936	0.936	0.055	0.057	0.257
Cambodia	0.049	0.049	0.234	0.904	0.935	0.934	0.045	0.046	0.219
Egypt, Arab Rep.	0.047	0.047	0.227	0.896	0.935	0.935	0.042	0.044	0.212
Vietnam	0.043	0.043	0.211	0.895	0.935	0.935	0.039	0.040	0.197
Philippines	0.040	0.040	0.198	0.900	0.936	0.936	0.036	0.037	0.185
Pakistan	0.038	0.038	0.193	0.900	0.936	0.936	0.035	0.036	0.181
Indonesia	0.036	0.036	0.181	0.899	0.936	0.936	0.032	0.033	0.170
China	0.033	0.033	0.172	0.892	0.933	0.933	0.030	0.031	0.160
Yemen, Rep.	0.029	0.029	0.153	0.897	0.935	0.935	0.026	0.027	0.143
India	0.021	0.021	0.117	0.897	0.935	0.935	0.018	0.019	0.110
Bangladesh	0.019	0.019	0.112	0.893	0.934	0.934	0.017	0.018	0.105

Source: Authors' compilation.

On average, the overall energy efficiency ranged from 10% to 75%, suggesting a wide variation across BRI countries (Of the 48 countries, about 50% lie below the average energy efficiency). The average energy efficiency score was 43%, which is generally low, except for Brunei Darussalam (77%), Singapore (73%), the United Arab Emirates (70%), Estonia (69%), Slovenia (64%), and Cyprus (63%). For most of these countries, their per capita income was far above a high-income country's average, allowing them to invest in energy-efficiency-enhancing technologies. For example, Brunei Darussalam, with a population just over 400,000, enjoys a high standard of living and is ranked the nineteenth country with the highest per capita gross domestic product (GDP) in the world [63]. Singapore's export-oriented economy has a high degree of trade openness and technology innovation [64]. Slovenia, a country with a high per capita income, has invested substantially in energy efficiency over the past 12 years (Since 2008, the government of Slovenia has stopped the operations of certain energy intensive industries) [65].

In contrast, in Table 6, countries with a relatively low level of economic development such as Indonesia, China, India, Yemen, the Philippines, Pakistan, and Bangladesh are extremely below the average energy efficiency score. However, such countries have great potential for energy conservation once they experience rapid economic development and developments in energy technology [6], which is what the BRI seeks to offer.

As can be seen in Table 6, of the 48 countries, China's energy efficiency ranked 44th with a score of 16%, which was much lower than the overall mean efficiency score of 46%. Qi et al. [6] estimated the energy efficiency of 15 EU and 60 BRI countries, where China ranked 58th out of a total of 75 countries. Similarly, Zhang et al. [15] ranked China as 42nd out of 56 BRI countries. Thus, there is a significant gap between China and the energy efficiency of other BRI countries.

Additionally, the BRI countries (except for Brunei Darussalam) experience high levels of persistent inefficiency, which suggests that the energy issue is more structural in these countries. Thus, efficiency improvement will benefit more from long-term policies (that promote innovation and adoption of energy technology) than from short-term policies.

4.3. Energy Efficiency Convergence

Having established the energy efficiency performances of the BRI countries, we went on to examine if these countries were converging or diverging with respect to energy efficiency. Therefore, with the β -converge analysis, we investigated whether countries that lagged behind could catch up

with other countries in the long run, given whether or not some influential factors in the convergence process are examined. The results of the β -convergence, which are based on the total energy efficiency of the K–L–H model, are reported in Table 7.

Table 7. Energy efficiency convergence.

Variables	Pooled OLS	Fixed Effe	ect Model
variables	1 doica OLS	Without Controls	With Controls
LnOTE t-1	-0.00105 *	-0.183 ***	-0.157 ***
	(0.0005)	(0.015)	(0.015)
FDI			-0.00023
			(0.0002)
Indus			-0.0051 ***
			(0.0019)
Trade			0.0039 ***
			(0.0011)
Constant	-0.0007	-0.171 ***	-0.150 ***
	(0.0005)	(0.014)	(0.0173)
Obs.	1200	1200	1051
Number of ID	48	48	48

Note: Standard errors in parentheses *** p < 0.01, * p < 0.1. Source: Authors' compilation.

First, the pooled regression, representing unconditional converge has a coefficient of $lnOTE_{t-1}$ (i.e., the convergence rate) to be negative and significant at the 10% confidence level. Generally, this implies that the BRI countries exhibit some trend of convergence in energy efficiency. In other words, lagging countries are in some way catching up with the advance economies in the long run, which confirms the results of Han et al. [54] for BRI countries, but contradicts that of Adom et al. [8] for African countries.

Next, we controlled for some influential unobserved country effects and the coefficient of $lnOTE_{t-1}$ was still negative, but now highly significant at the 5% confidence level. This shows that the energy efficiency convergence among BRI countries is subject to country-specific effects such as technological level. Adom et al. [8] and Stern [12] found similar results for African countries.

Finally, we introduced our conditional variables: FDI, trade, and industrial structure in the model. The coefficient of the coefficient of lnOTE $_{\rm t-1}$ still remained negative and significant at the 5% confidence level. The coefficients for the industrial sector and FDI are negatively related to energy efficiency convergence, which shows that both variables cause divergence in efficiency, but the latter is insignificant. Trade, on the other hand, exerts a positive and significant impact on efficiency convergence, which implies that trade may speed up the convergence in energy efficiency. Han et al. [54] also found similar results for the BRI countries.

4.4. Discussion

It is clear from the results that energy efficiency varies widely across the BRI countries. High variability in efficiency clearly shows the presence of significant unobserved country heterogeneity in our sample data, and therefore should be controlled in efficiency modeling and specifications. Given that BRI countries perform much better in transient energy efficiency than in persistent energy efficiency suggests that the problem of energy inefficiency is more of a structural and long term issue. Thus, efforts that promote technological innovation should be given more attention. Considering that the BRI is to connect several countries and regions, it has the potential of transferring technical innovation from its source of origin to some different places through trade and FDI in the region. Therefore, policies that promote international trade and interaction should be given much attention.

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From the results, most high-income BRI countries perform much better than the lower-income countries, probably because of economic growth level, better technology, improved management systems, less energy intensive industries, and use of cleaner energy.

Regarding the energy efficiency convergence, the BRI countries are generally converging, but the rate of convergence is influenced by an increase in trading activities. Trade has the potential to reduce energy intensity through technological transfer and adoption [66]. Thus, major technological breakthroughs may be expedited by greater trading activities, which may improve end-use energy efficiency. Hübler [67] examined the effect of trade on energy consumption and concluded that trade could increase energy-saving technology and reduce energy consumption. However, the industrial structure slows the efficiency convergence rate in the region. Within the BRI region, the industrialization process accounts for a large number of secondary industries, which turns out to be energy-intensive and emit more greenhouse gas.

Concerning the insignificant effect of FDI on efficiency convergence; first, this may be due to poor human capital development, particularly in low-income countries where domestic firms are unable to effectively absorb FDI technologies. Thus, FDI is not likely to be beneficial enough to reduce the technological gap and efficiency convergence of BRI countries. This outcome shows the need to improve human capital and absorptive ability, particularly in low-income BRI countries. Second, due to weak environmental regulations in developing countries [68,69], FDI may fail to increase energy efficiency, which confirms the "pollution haven" hypothesis. According to the hypothesis, pollution-intensive industries tend to migrate from developed countries to underdeveloped countries due to the less stringent environmental regulations in underdeveloped countries.

5. Conclusions and Policy Recommendations

In this paper, we attempted two things: first, we estimated the total energy efficiency for 48 BRI countries by differentiating between transient and persistent energy efficiency using a series of models. Next, we investigated the beta convergence of efficiency for the BRI countries as well as the possible influencing factors. The major findings are as follows:

- (1) In the energy demand frontier function, we found that while rising energy price, population density, service sector, and technical change reduces energy consumption, high economic activities, growing urban population, and the industrial sector increases it.
- (2) Persistent inefficiencies are much higher than transient inefficiencies, suggesting a more structural energy problem in the BRI countries, which can be addressed with long-term policies such as an increase in technical progress.
- (3) Energy efficiency varies widely across the BRI countries, suggesting the presence of significant unobserved country heterogeneity.
- (4) We found evidence of energy efficiency convergence, but the convergence rate accelerates even more when there is an increase in trade in the BRI countries. The industrial sector, on the other hand, slows the convergence rate, and FDI does not affect the convergence process.
 - Based on these findings, we propose the following policy implications:
- 1. BRI countries (both high and low-income countries) need to increase energy technology to significantly reduce persistent inefficiency. Under the BRI, more investments should go into energy-related infrastructure to increase technological progress.
- 2. The level of human capital may be low in BRI countries. Low-income countries must therefore focus more on developing their human capital in order to improve their ability to absorb technological diffusion from FDI and trade to reduce the technological gap and speed up the energy efficiency convergence
- 3. Considering the different resource endowment of each BRI country, with mutual cooperation under the BRI, China and the Middle East oil-producing countries can improve energy

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efficiency and security. For instance, China's investment in energy projects such as oil and gas pipelines, nuclear power, and liquefied natural gas terminals may create a better and more energy-efficient network (https://theasiadialogue.com/2018/03/30/chinas-energy-revolution-strategy-opportunities-and-challenges/). Additionally, the construction of these liquefied natural gas terminals and gas pipelines will enable Qatar, Iran, Indonesia, and Australia to increase the production of natural gas as a cleaner substitute for coal and oil.

- 4. Since the industrial sector of the BRI region is energy-intensive, efforts to invest in less energy-intensive industrial technology should be a priority in the BRI region. This can be done by setting up research and development (R&D) funds (if not yet done) and provide low-interest loans for entrepreneurs investing in energy R&D projects. Furthermore, like in Slovenia, countries should take a deliberate step to stop operations of some energy intensive industries.
- 5. Considering that some developing countries (e.g., China) restrict imports from developed countries, especially those of high-tech goods [70], it is appropriate that these policies be revised under the BRI to encourage transfers of innovation, technology, and spillover activities.
- Last, but not least, BRI countries (especially the developing ones) should raise the threshold of
 entry for dirty industries, control exports of pollution and energy-intensive industries, or develop
 new export competitive advantages.

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Appendix A

Table A1. Sample Belt and Road Initiative Countries.

Southeast Asia	Central & Eastern Europe	Middle East & Africa	South Asia	Northeast Asia	Central Asia
Vietnam	Ukraine	Egypt	Sri Lanka	China	Kyrgyz Rep.
Thailand	Turkey	Israel	Pakistan	Mongolia	Kazakhstan
Singapore	Slovak Republic	Jordan	India		Tajikistan
Philippines	Slovenia	Lebanon	Bangladesh		Georgia
Malaysia	Albania	Oman	Nepal		Azerbaijan
Indonesia	Belarus	Saudi Arabia	-		
Cambodia	Bosnia &	United Arab			
Cambodia	Herzegovina	Emirates			
Brunei Darussalam	Bulgaria	Iran			
	Croatia	Yemen			
	Estonia				
	Czech Republic				
	Moldova				
	Lithuania				
	Latvia				
	Hungary				
	Cyprus				
	Russia				
	Romania				
	Poland				
8	19	9	5	2	5

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	Coeffi	cients	(b-B)	sqrt(diag(V_b-V_B))	
	(b) Fixed	(B) Random	Difference	(S.E.)	
InPrice	-0.0343283	-0.0236043	-0.010724	0.0027465	
lnGDP	0.255418	0.2279398	0.0274782	0.006843	
LnPD	-0.2302651	-0.2143666	-0.0158985	0.0271285	
Service	-0.006711	-0.0062211	-0.0004899	0.0002204	
Indus	0.0019625	0.0025773	-0.0006147	0.0002536	
Time	-0.0145202	-0.0134028	-0.0011174	0.0006685	

Table A2. Hausman test.

b = consistent under Ho and Ha; obtained from xtreg. B = inconsistent under Ha, efficient under Ho; obtained from xtreg. Test: Ho: difference in coefficients not systematic. $Chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 36.00$. Prob>chi2 = 0.0000.

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