Volume and Issues Obtainable at Center for Sustainability Research and Consultancy

Review of Economics and Development Studies
ISSN: 2519-9692 (E): 2519-9706
Volume 3: Issue 2 December 2017
Journal homepage: www.publishing.globalcsrc.org/reads

Measuring Energy Efficiency and Exploring the Determinants of Energy Efficiency in Selected Economies of Asia

[1]Muhammad Nadeem, [2]Hafiz Ghulam Mujaddid, [3]Nabila Asghar

[1]PhD Scholar, National College of Business Administration & Economics, Pakistan
[2]Associate Research Fellow, Punjab Economic Research Institute, Pakistan
[3]Assistant Professor, Department of Economics, University of the Punjab, Pakistan.

ARTICLE DETAILS

History
Revised format: Nov 2017
Available Online: Dec 2017

Keywords
Energy Efficiency,
DEA Double Bootstrap, s,
Asia.

JEL Codes: *P28*

ABSTRACT

Purpose: There is widely recognition of the need to effectively consume the energy, particularly in energy deficient countries. The effective use of energy requires that one must know the current efficiency level, so appropriate measures may be taken to make the efficient use of energy. Present study in an attempt to measure the energy efficiency and determinants of energy efficiency in fourteen selected developing economies of Asia for the time period 2007 to 2013. DEA double bootstrap technique has been used for estimation purposes. The results of bias corrected energy efficiency indicate that there is not even a single economy that is fully energy efficient over the period under consideration. After measuring the energy efficiency, truncated regression analysis is utilized to find the determinants of energy efficiency. The results indicate that industrial share and per capita income have positive effect on energy efficiency, while corruption, political instability and voice and accountability have negative impact on energy efficiency. So there is dire need to control corruption, political stability needs to be resorted and voice and accountability system needs to be redefined.

Corresponding author's email address: mnadeem.eco@gmail.com

Recommended citation: Nadeem, M., Mujaddid, G. & Asghar, N., (2017). Measuring Energy Efficiency and Exploring the Determinants of Energy Efficiency in Selected Economies of Asia. *Review of Economics and Development Studies, 3*(2) 135-146. **DOI:** https://doi.org/10.26710/reads.v3i2.172

1. Introduction

Energy efficiency measurement has become an important component of energy strategy in many countries, especially the energy-deficient ones. Many countries recognized the need to understand, how effectively energy was being consumed in their economies, so that they can increase energy efficiency. To serve these purposes, there is need to measure the energy efficiency with an appropriate technique and then its determinants to show the variation in energy efficiency. Efficiency analysis is also used in cross country comparisons to explain differences in energy performance among countries and for international benchmarking.

Energy intensity and energy efficiency are the two well-known energy efficiency indicators that are commonly used in macro level policy analysis. Energy intensity is defined as the energy consumption divided by the economic output, and energy efficiency is the reciprocal of energy intensity. These traditional energy efficiency indicators take energy consumption in to account as a single input that produces an economic output as no output would be produced by using a single energy input, without any other inputs (see, e.g., Mukherjee, 2008b); therefore, some other key inputs are ignored, such as capital and labor. Energy consumption must be combined with other inputs to produce an economic output, and Zhang et al., (2011) said that substitution effects exist between energy and other input factors (e.g., labor and capital stock). If energy consumption is evaluated in terms of partial factor energy efficiency, the result is a misleading estimate (Hu and Wang, 2006). To overcome the disadvantage of partial factor energy efficiency, an increasing number of researchers have devoted themselves to analyzing the total factor energy efficiency using DEA.

Zhou et al. (2008) gave an extensive review of 100 studies published from 1983 to 2006 that have used DEA methodology in energy and environmental studies. According to that survey, 72 of these publications were made between 1999 and 2006, which indicates a rapid increase in using DEA methodology, while they also indicated the use of bootstrap technique of Simar and Wilson (1998), which is used to conduct a sensitivity analysis on the DEA efficiency scores.

There are two general approaches to measure the efficiency: parametric and nonparametric. The parametric approach requires specifying and estimating a parametric production or cost frontier. The main strength of the parametric or stochastic frontier analysis (SFA) is its incorporation of stochastic error, and therefore allowing for hypothesis testing. The disadvantage of this approach is the need of imposing an explicit functional form and distributional assumption of the error term. Hence, the SFA is sensitive to the selection of the parametric functional form.

The nonparametric approach, e.g. Data Envelopment Analysis, has the advantage of imposing no prior parametric restrictions on the technology and thus is less sensitive to misspecification. It is also not subject to assumptions on the distribution of the error term. However, because DEA is a deterministic approach, all deviations from the estimated frontier are assumed to be the result of inefficiency, making it sensitive to measurement errors and data noises. To overcome the limitations of the deterministic nature, bootstrapping methods can be used to produce confidence intervals for the efficiency estimates and allow hypothesis testing.

In explaining variation in efficiency, a second-stage regression analysis is typically used to examine the effect of environmental factors on the estimated efficiency. Chilingerian (1995), Ruggiero and Vitaliano (1999), and Mukherjee (2008a), among others, carried out the second-stage regression analysis. According to Simar and Wilson (2007), the coefficient estimates obtained by the above studies may not be consistent, since these studies used OLS and/or Tobit regression and have not taken into account the serial correlation of the efficiency estimates. Instead, Simar and Wilson (2007) propose a double bootstrap procedure which can produce consistent estimates of the regression coefficients and provide valid confidence intervals for the estimates. In the present paper, the double bootstrap will be adapted and applied to our regression analysis.

However, it is not sufficient to measure the energy efficiency only without determining its sources. This study measures energy efficiency scores of Asian developing countries and also assesses its determinants. There is hardly any study that has estimated bias-corrected energy efficiency scores of Asian developing countries and also considered its sources. This will be the perhaps the first study to evaluate the energy efficiency and its determinants by applying the DEA double bootstrap.

The remaining of the study is ordered as follows: Review of literature is given in section II. Section III provides methodological framework and describes sources of data. Empirical results are interpreted in Section IV. Section V consists of conclusions and policy recommendations.

2. Review of Literature

Geller et al., (2006) critically analyzed the energy intensity behavior for major OECD countries from 1973 to 2002. They tried to evaluate that reduction in energy intensity was because of energy efficiency or because of structural change. They also analyzed the policies related to the energy efficiency and concluded that well planned policies could produce result in the form of energy saving. They presented the case of USA and found that 9 policies reduced energy usage almost 11% in 2002 and the same result was showed for Japan, California and European Union. They recommended that minimum efficiency standards would be maintained and consumer behavior needed to be changed toward the less usage of energy appliances etc.

Ang (2006) critically analyzed the various energy efficiency indicators like energy intensity, energy coefficient and energy elasticity and found that these indicators were misleading to determine the energy efficiency. He briefly discussed the energy intensity to define that it is not worthwhile due to the denominator, GDP, which lieu of different activities and further explored that change of energy intensity rather better than simple energy intensity. After finding these indicators wrong, he used the index decomposition analysis to derive the economy-wide composite energy efficiency and concluded that this composite energy index is better than classical energy efficiency indicators.

Hu and Kao (2007) measured the energy efficiency for seventeen APEC countries over the period of 1991 to 2000. The applied the input oriented DEA for measuring the energy efficiency in the framework of total factor by utilizing the three inputs (labor, capital and energy) and one output (GDP) and then suggested the energy saving targets (EST) for APEC economies in every year from 1991 to 2000. They found that China was less energy efficient i.e. it has largest EST while Hong Kong, Philippine and USA has lowest EST i.e. they are highly energy efficient. They also found that there was generally increasing trend of energy efficiency in APEC economies.

Lee and Chang (2008) tried to find out the causal relationship between GDP at constant prices and the energy consumption by taking the data of sixteen Asian countries for the period of 1971-2002. They applied the heterogeneous panel co-integration and panel based ECM to analyze the causal relationship between these core variables within multivariate function in which capital formation was used as a proxy of capital input and labor was taken another input. They found in long run that there was positive unidirectional co-integrated relationship from energy consumption to GDP at constant prices by taking the heterogeneity effect of countries while there was not any causal relationship in short run. The same result was found after dividing the Asian countries in regional groups like APEC and ASEAN.

Zhou and Ang. (2008) measured the energy efficiency of 21 OECD economies for the period of 1997 to 2001. They applied DEA linear programming models to construct economy wide energy efficiency index for measuring the energy efficiency by using six inputs (capital stock and labor force as non-energy inputs and coal, oil, gas and other energy as energy inputs) and two outputs (GDP as desirable output while CO_2 as undesirable output). They compared the results of energy efficiency performance index and weighted average energy utilization performance index and found that latter one have greater discriminating power as it also included the energy mix effects. They found that mean energy efficiency of countries had been changed over the period of time under both index versions.

Honma and Hu (2008) measured the energy efficiency in total factor framework of forty seven administrative regions in Japan over the period of 1993 to 2003. They used the DEA for computing energy efficiency by using 14 inputs, including 11 energy inputs, and one output (regional GDP). They found that 29 administrative regions were fully efficient out of 47 prefectures over the entire period of time in case of overall technical efficiency scores and found that these regions had shared same features. They also estimated the connection between energy efficiency and per capita income after dividing the regions in four categories (low, lower middle, upper middle and high income) and discovered the U-

shaped relation between energy efficiency and per capita income.
Wei et al. (2009) measured the energy efficiency of 29 provinces of China over the period of 1997-2006. They applied DEA to estimate the energy efficiency index by using three inputs (labor, capital and energy consumption) and one output (GDP) and found that there were highly differences in energy efficiency of all provinces. Further, they tried to find out the impact of different determinants on the level of energy efficiency in regression analysis and found that government expenditure, state owned economic portion and industry share in GDP had negative impact on energy efficiency while technical level and non-coal part in energy consumption had positive impact on energy efficiency.

Zhang et al., (2011) measured the energy efficiency of 23 developing countries over the period of 1980 to 2005. They used the DEA window for energy efficiency analysis by utilizing the three inputs (labor, capital and energy consumption) and one output (GDP). They found that there was prominent variation in the score of total factor energy efficiency relating to different developing countries. They found that Syria, Kenya, Philippine and Sri Lanka showed worst performance in energy efficiency and China was the rapid growing country among the countries which had the increasing trend in energy efficiency. Further, they applied the Tobit Regression to find out the relationship between income per capita and energy efficiency and found that there was u-shaped relationship between them.

Zhou et al., (2012) measured the economy wide energy efficiency of 21 OECD countries for the year of 2001. They applied the stochastic frontier approach (SFA) to measure the energy efficiency index from the production point of view by utilizing the three inputs (labor, capital and energy) and one output (GDP). They also used the DEA technique to measure the energy efficiency index for the purpose of making comparison between both techniques. They found that only Italy was the fully efficient country in case of SFA and six countries were efficient in case of DEA by following the VRS. So, they concluded that SFA presented the more consistent and robust results as compare to DEA.

Song et al. (2013) measured the energy efficiency of BRICS' countries by taking the data over the period of 2009 and 2010. They employed the Super-SBM model to measure the energy efficiency by utilizing the three inputs (labor, capital and energy consumption) and one output (nominal GDP). They also bootstrapped the efficiency scores of DEA and finally, measured the connection between energy efficiency and carbon emission. It is found that overall BRICS' economies have low energy efficiency but increasing trend over the period of time and China was the most efficient country with respect to energy efficiency among them. They also found that the impact of carbon emission on energy efficiency vary from one economy to other economy due to the varying energy structure of each country.

3. Methodology

Charnes et al.,'s (1978) and Fare et al.,'s (1985) linear programming models provided the base for the production efficiency analysis. Those techniques are known as data envelopment analysis (DEA), where the convexity assumption is adopted in the literature. Charnes, Cooper, and Rhodes (1978) developed the DEA and further modified by Banker et al., in 1984 which based on the frontier efficiency concept first defined by Farrell (1957). It is a non-parametric technique and used for measuring the efficiency of decision making units. It does not demand assumption of any specific functional form with respect to the inputs and outputs or the setting of weights for the various factors. DEA creates an efficient frontier for every observation. The maximum output can be obtained empirically by a given set of inputs. We are not going to take general overview of DEA here, for this see Coelli et al. (2005).

3.1 Data Envelopment Analysis and double bootstrap

The output oriented variable returns to scale (VRS) model will be employed for measuring the technical energy efficiency estimates because constant returns to scale (CRS) is utilized where economies or different sectors operate at their optimal scale. There is various considerable events relating to this study which show that economies are not working at their optimal scale due to the presence of national constraints, different size of economies, and imperfect competition among the economies. For each and every country, output oriented DEA energy efficiency estimator $\hat{\theta}_{ivrs}$ can be attained for any data set (X_i, Y_i) by solving the coming linear programming equation.

$$\hat{\theta}_{ivrs} = max(\theta > 0|\theta iYi \leq \sum_{i=1}^{n} ¥iYi; Xi \geq \sum_{i=1}^{n} ¥iXi; \sum_{i=1}^{n} ¥i = 1; ¥i \geq 0, i = 1, \ldots .n) \quad (1)$$

In equation (1), X and Y are used as inputs and outputs respectively and i=1…..,n is the specific country. The θiYi is the efficient level of output, θ is the scalar and $¥i$ is the non-negative vector of constant defining the optimal weights of inputs to outputs. The attained value of $\hat{\theta}_{ivrs}$ is the technical energy efficiency estimate for ith country. In case of output oriented, output should be increased for getting the higher technical energy efficiency by a given set of inputs where $\hat{\theta}_{ivrs}$=1 means that the economy is considered fully efficient while $\hat{\theta}_{ivrs}$<1 means that the economy is not fully efficient and it is required to enhance output from the given set of inputs for reducing the inefficiencies for each economy.

There are two things to be noted relating to the above equation (1). First, in the linear program, VRS is assumed and second, Simar and Wilson (2000) observe that $\hat{\theta}_{\mathbf{vrsi}}$ is the downward biased estimator, as economy frontier can be underestimated. Due to limitations of DEA, the smooth bootstrap technique of Simar and Wilson (1998, 2000) is applied in this study for getting the bias-corrected energy efficiencies and their confidence intervals accompanied by the DEA with bootstrapping approach.

The estimated bias-corrected energy efficiencies in the first stage are left truncated by 1. In the second stage, a single truncated regression with bootstrap will be employed for regressing these efficiency scores of all countries against a set of explanatory factors in the following truncated maximum likelihood regression model.

$$\hat{\theta}vrs_i = b + z_i\beta + \varepsilon_i \quad (2)$$

In Eq. (2), b is the constant term, ε_i is statistical noise, and z_i is a vector of specific variables (these are known as environmental variables) for economy *i* that is expected to be related to the economy's efficiency score.

3.2 Why double bootstrap?

There appear only few results for the sampling distribution of interest. This is for this reason that bootstrap techniques are adopted by Simar and Wilson (2000, 2007). The concept behind the bootstrapping is very simple i.e. Simulate the sampling distribution of any specific object by mimicking the data generating process (DGP). The DGP that gives the logic for Simar and Wilson's (2007) double bootstrap is the DEA model represented by eq. (1) and the second step truncated regression described by Eq. (2).

To apply the bootstrap procedure, it is assumed that the original sample data is produced by the DGP and that we can simulate the DGP by using the 'new' or pseudo data set that is derived from the actual data set. Then DEA model is re-estimated by incorporating this new data set. It is possible to derive an empirical distribution of bootstrapped values by doing this process again and again which provides a Monte Carlo approximation of the sampling distribution and also help out in inference measures. The efficiency of the bootstrapped methodology and the consistency of the statistical inference significantly depend on how well it specifies the true DGP and on the exact re-sampling simulation to copy the DGP.

The Simar and Wilson's (2007) algorithm 2 of bootstrap procedure is employed in this study that provides inference about coefficients and consist of the following seven steps.
Step 1- Calculate the DEA output oriented efficiency score $\hat{\theta}ivrs$ for each and every economy in sample data set, using Equation (1).

Step 2- Maximum likelihood method is used to calculate the truncated regression of $\widehat{\Theta}ivrs$ on z_i to estimate the $\hat{\beta}$and $\hat{\sigma}$

Step 3- for each economy i=1…, n, repeat the coming four steps (a-d) N times to yield a bootstrap estimate ($\hat{\Theta}_{i,b}$ b=1….N)

- **a)** Draw ε_i for each i=1…,n, from N(0, $\hat{\sigma}_\varepsilon$) with left truncation.
- **b)** Calculate $\Theta^* = z_i\hat{\beta} + \varepsilon_i$ for each i=1…, n.
- **c)** Generate a pseudo data set (x_i^*, y_i^*), where $xi*$ □□xi and y_i^* is $y_i[\widehat{\Theta}/\Theta^*]$
- **d)** By using this pseudo set and Eq. (1), calculate a new DEA estimate $\widehat{\Theta}^*$ for each industry

Step 4- Biased corrected estimator $\hat{\hat{\Theta}}$ is calculated for each industry i=1…, n as $\hat{\hat{\Theta}}$= $\hat{\Theta}$- bias ($\hat{\Theta}_i$) where the bias term is calculated by the following Simar and Wilson's (2000) method.

$$1/N\ [\sum_{b=1}^{N} \widehat{\Theta} *] - \hat{\Theta}_i$$

Step 5- Maximum likelihood method is employed to calculate the truncated regression $\hat{\hat{\Theta}}_i$ on z_i to provide the $\hat{\hat{\beta}}$and $\hat{\hat{\sigma}}$

Step 6- Repeat the next three steps (a-c) N_2 times for getting the bootstrap estimates [{$\hat{\hat{\beta}}_b^*$ and $\hat{\hat{\sigma}}_b^*$, b=1…N_2}]

- **a)** Draw ε_i for each i=1..., n, from N (0, $\hat{\hat{\sigma}}$) with left truncation.
- **b)** Compute $\Theta^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i$ for each i=1…., n.
- **c)** For estimating the truncated regression θ_i^{**}on z_i, again the maximum likelihood method is used for getting the $\widehat{\hat{\hat{\beta}}*}$ and $\widehat{\hat{\theta}^*}$

Step 7- use the bootstrap results to construct the estimated confidence interval for each element of $\hat{\beta}$and $\hat{\sigma}_\varepsilon$.

3.3 Selection of data

Different inputs and outputs are incorporated in various studies for energy efficiency analysis but in this study three inputs (total labor force, gross fixed capital formation and energy consumption) and one output (real GDP) are selected for measuring efficiency. Data has been collected for following countries: Bangladesh, China, India, Indonesia, Japan, Korea, Rep., Malaysia, Nepal, Pakistan, Philippines, Sri Lanka, Kazakhstan, Thailand and Turkey from 2007 to 2013 from World Development Indicators (WDI) and World Governance Indicators (WGI). Data for percentage of industrial share in GDP, per capita income as determinants of energy efficiency is collected from WDI while data for corruption, political instability and voice and accountability is collected from World Governance Indicator. One dummy variable is introduced to check the impact of financial crisis for 2008 and 2009.

4. Estimations and interpretation of results

In the first step of the DEA double bootstrap technique, original DEA and bootstrapped VRS technical energy efficiencies of 2007 to 2013 are estimated and presented in table 4.1 along with confidence intervals. As it can be noted that original DEA energy efficiency estimates exaggerate the efficiency scores and underestimate the frontier as Simar and Wilson (2000) describe the limitations of DEA and it can also be seen from estimated results that DEA exaggerates the results while bias-corrected efficiencies (which is referred as BC in the following table) which are obtained after 2500 simulations, correct the energy efficiency scores and remove the biasness of exaggeration from the results. The main feature of these estimations is that they also lie in the following confidence intervals while DEA does not lie in the interval because it underestimates the frontier and it is assumed to touch the frontier before reaching to the actual one.

As in this study output oriented DEA Bootstrap technique is used to measure the energy efficiency estimates in 1st stage, the energy efficiency score 1 represents the technically fully energy efficient country while estimated efficiency score less than 1 shows the inefficient or less energy efficient country.

In case of output oriented model, different set of output is produced by utilizing same set of inputs. So, for minimizing the inefficiencies, maximum level of output should be obtained with the fixed set of inputs. Table 4.1 shows the results of Asian developing countries for the period of 2007 to 2013 and it is found that there is not any country is fully efficient over the whole period in case of bias corrected technical energy efficiency case while some are fully efficient in case of DEA because DEA exaggerates the estimates as Simar and Wilson (2000) described the deficiency of DEA. It can be noted that after 2007 the energy efficiency started to deteriorate over the period then it is improved in 2013. This phenomenon depicts the picture of worldwide crisis.

Table 4.1 Energy Efficiency Analysis

2007					**2008**			
Countries	**DEA**	**B.C**	**L.C.I**	**U.C.I**	**DEA**	**B.C**	**L.C.I**	**U.C.I**
Bangladesh	0.8147	0.7466855	0.7049718	0.8085351	0.7764	0.717208	0.675926	0.771183
China	0.611	0.5454791	0.4788696	0.6090306	0.6769	0.600731	0.526126	0.674622
India	0.6503	0.5990432	0.5517696	0.6472582	0.6312	0.57233	0.520944	0.627563
Indonesia	0.8904	0.8394061	0.7924678	0.8854621	0.8169	0.768	0.720298	0.812643
Japan	1	0.8035931	0.7221317	0.9942838	1	0.790011	0.724145	0.99207
Korea, Rep.	0.7362	0.6570292	0.580497	0.7328023	0.754	0.665587	0.588492	0.749456
Malaysia	0.9558	0.8810419	0.8186481	0.9481437	0.9408	0.853973	0.784886	0.935699
Nepal	1	0.7952495	0.7190051	0.9928826	1	0.802878	0.731563	0.993966
Pakistan	1	0.9069138	0.8587288	0.9932097	0.9863	0.923038	0.875396	0.982835
Philippines	1	0.8932272	0.8532178	0.993043	1	0.908356	0.86481	0.994528
Sri Lanka	1	0.7994816	0.7225366	0.9932115	1	0.800394	0.727834	0.99384
Kazakhstan	1	0.7909445	0.7155708	0.9931344	1	0.80265	0.728547	0.994174
Thailand	0.7572	0.7058573	0.6667255	0.7517825	0.7405	0.688295	0.644456	0.736602
Turkey	0.9935	0.9181041	0.8348563	0.9881067	1	0.891898	0.812063	0.992503
2009					**2010**			
Countries	**DEA**	**B.C**	**L.C.I**	**U.C.I**	**DEA**	**B.C**	**L.C.I**	**U.C.I**
Bangladesh	0.6662	0.5969471	0.5514523	0.6618626	0.6982	0.645896	0.600475	0.69383
China	0.7825	0.68069	0.5994283	0.7793586	0.8259	0.729616	0.647497	0.822793
India	0.5929	0.5214461	0.4689217	0.5884747	0.5725	0.509189	0.455196	0.569293
Indonesia	0.7069	0.6359407	0.5896416	0.7042212	0.7384	0.685468	0.635568	0.733382
Japan	1	0.7699991	0.7122666	0.9936523	1	0.786615	0.704416	0.992941
Korea, Rep.	0.8063	0.7021661	0.6217361	0.8020098	0.8115	0.717613	0.636419	0.807394
Malaysia	0.8798	0.7700526	0.713286	0.8735322	0.846	0.756669	0.699087	0.84072
Nepal	1	0.7587046	0.7071755	0.9921747	1	0.780021	0.704655	0.993805
Pakistan	0.959	0.9068784	0.8440546	0.9552358	1	0.86981	0.832173	0.993249
Philippines	0.9277	0.8391772	0.7837231	0.9213646	0.8951	0.82381	0.772612	0.889495
Sri Lanka	1	0.7656681	0.7087986	0.9908921	1	0.779936	0.704582	0.993145
Kazakhstan	1	0.7649023	0.7086195	0.9929301	1	0.786066	0.719634	0.992417
Thailand	0.689	0.6221809	0.5770155	0.6846391	0.7267	0.673793	0.629442	0.721585
Turkey	1	0.8249288	0.7745067	0.9911749	0.9187	0.820792	0.744058	0.913905
2011					**2012**			
Countries	**DEA**	**B.C**	**L.C.I**	**U.C.I**	**DEA**	**B.C**	**L.C.I**	**U.C.I**
Bangladesh	0.6769	0.6187904	0.5736447	0.6730917	0.661	0.600994	0.557009	0.65553
China	0.9068	0.7937536	0.6979605	0.9037735	0.9594	0.834806	0.731454	0.955838

India	0.5526	0.4870692	0.429626	0.5493933	0.5912	0.520515	0.466263	0.587899
Indonesia	0.7236	0.6643505	0.6213525	0.7187602	0.7112	0.650174	0.601712	0.706442
Japan	1	0.770108	0.6981184	0.9925896	1	0.769451	0.709901	0.992156
Korea, Rep.	0.8112	0.7096623	0.6240787	0.8061854	0.7949	0.693905	0.611705	0.790652
Malaysia	0.8571	0.7662175	0.7027779	0.8523573	0.77	0.689114	0.634486	0.765236
Nepal	1	0.7635888	0.6943807	0.9936462	1	0.762387	0.705296	0.992829
Pakistan	1	0.8181079	0.7816129	0.9911871	1	0.802651	0.774558	0.991518
Philippines	0.9329	0.8481874	0.7964991	0.9254411	0.9071	0.822915	0.774819	0.9008
Sri Lanka	1	0.7697861	0.6940674	0.9916921	1	0.760755	0.70785	0.991078
Kazakhstan	1	0.7821048	0.7265472	0.9929896	0.9359	0.829687	0.755712	0.928971
Thailand	0.7018	0.6432762	0.6011947	0.695855	0.6779	0.621949	0.577734	0.673496
Turkey	0.8602	0.7622903	0.6911074	0.8552647	0.9152	0.814587	0.738052	0.908154

2013				
Countries	**DEA**	**B.C**	**L.C.I**	**U.C.I**
Bangladesh	1	0.805783	0.7301953	0.9916419
China	1	0.8868376	0.7874117	0.99449
India	0.6222	0.5612354	0.5063505	0.619421
Indonesia	0.7228	0.6680684	0.6258928	0.7195072
Japan	1	0.8094719	0.7291745	0.9932399
Korea, Rep.	0.7965	0.7126335	0.6333099	0.7930702
Malaysia	0.7551	0.6876535	0.6336349	0.7508115
Nepal	1	0.8078452	0.7282896	0.9947478
Pakistan	1	0.8165499	0.7594116	0.9935376
Philippines	0.8875	0.8123746	0.7593071	0.8817132
Sri Lanka	1	0.8018071	0.7251	0.99253
Kazakhstan	0.9035	0.8181752	0.7526585	0.8969229
Thailand	0.7078	0.6561069	0.6169624	0.7033867
Turkey	0.9271	0.8410899	0.7690203	0.9222657

Table No 4.2 Determinants of VRS Technical Energy Efficiency, Using a Bootstrapped Truncated Regression

Regressors	**B-hats**	**S.E**	**T-statistics**
Constant	**2.219074**	**0.3976863**	**5.579960889**
IND	**0.01989284**	**0.01130489**	**1.759666834**
Corruption	**-0.01431264**	**0.007440124**	**-1.923709874**
Political ins	**-0.03894633**	**0.01182374**	**-3.293909541**
Voice&Acc	**-0.01350435**	**0.00651368**	**-2.073228958**
PCI	**7.3932E-05**	**2.81962E-05**	**2.622058378**
FDM	**0.0295248**	**0.1960464**	**0.150601082**

After measuring the bias-corrected technical energy efficiency of the fourteen Asian developing countries for the period of 2007 to 2013, the energy efficiencies of 14 countries for seven years are pooled in one truncated regression form as showed in equation (2) and maximum likelihood method is applied for truncated regression as discussed in the second step of the Simar and Wilson's (2007) double bootstrap process. Results of determinants of VRS energy technical efficiency, standard errors and t statistics are presented respectively in column 2, 3 and 4 of table 4.2.

In the results of second stage, where coefficients are bootstrapped 2500 times, some interesting results are found in the scenario of this study. It is found that percentage of industrial share in GDP has positive relation with energy efficiency and per capita income (PCI) also has positive relation with energy efficiency. Increase in industrial share may enhance energy efficiency due to the reason that as industrial share increases, economies of scales will be achieved which will enhance energy efficiency. Increase in industrial share may also enhance per capita income which also has been found enhancing the energy efficiency. Zhang et al. (2011) found U-shaped relationship between total factor energy efficiency and gross national income per capita which showed income per capita had negative impact initially due to the industrial growth until a certain point. But U-shape relation showed that energy efficiency will increase after certain point due to the increase of per capita income. In present study there is no evidence of U-shape relation between energy efficiency and per capita income which may be due to the reason that most of the economies under consideration are emerging economies and they may have already achieved that certain point of industrial growth so there is only positive relation found. Corruption has been found negatively related to the energy efficiency which may be due to the reason that corruption promotes malpractices and retards efficiency. Fredriksson et al. (2004) explained that corruptibility of policy makers will reduce the energy policy stringency. It is found that political instability also has negative impact on energy efficiency which may be considered according to expectations as more political instability leads to a volatile socio-economic environment which disrupts the efficient use of energy. Voice and accountability depicts very interesting and surprising result which indicates that voice and accountability has negative and significant effect on energy efficiency. As proxy for voice and accountability used in this study is defined as *voice and accountability Reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media*. Voice and accountability may have negative impact due to improper use of these rights. Lastly the dummy used for the financial crises depicts no significant impact in this study.

5. Conclusion

This study has been aimed to estimate the technical energy efficiency of fourteen selected Asian countries for the period of 2007 to 2013. As energy efficiency measurement has become an important component of energy strategy in many countries, especially for the energy-deficient countries. So every government is concerned to analyze the energy efficiency and to know how well its economy is energy efficient, so they may find the ways to make efficient use of energy. There are numerous techniques to measure the energy efficiency while DEA double bootstrap is applied to measure the technical energy efficiency and its determinants in this study because of its superiority over other existing techniques. DEA double bootstrap approach measures the bias-corrected energy efficiency scores and determinants of efficiency. While DEA measures the biased efficiencies and it exaggerates the efficiency scores as can be observed from present study that DEA energy efficiency scores do not lie in the confidence interval and these scores are beyond the interval due to the bias which exists in DEA scores while bootstrapped efficiency scores lie within the confidence interval and these are bootstrapped by 2500 iterations.

The results indicate that no country is fully energy efficient over the whole period of estimations in case of bias corrected energy efficiency. It is found that energy efficiency of every country deteriorated over the period of time then started to rise in last period. After measuring the energy efficiency, truncated regression analysis is utilized to find the determinants of energy efficiency.

In second stage, coefficients are bootstrapped 2500 times, it is found that industrial share and per capita income have positive effect on energy efficiency while corruption, political instability and voice and accountability have negative impact on energy efficiency. It is found in this study that dummy of financial crises has not any significant impact.

References

Ang, B. W. (2006). Monitoring changes in economy-wide energy efficiency: from energy–GDP ratio to composite efficiency index. *Energy Policy*, *34*(5), 574-582.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis.*Management science*, *30*(9), 1078-1092.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444.

Chilingerian, J. A. (1995). Evaluating physician efficiency in hospitals: A multivariate analysis of best practices. *European Journal of Operational Research*, *80*(3), 548-574.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer.

Fare, R., Grosskopf, S., & Lovell, C. K. (1985). *The measurement of efficiency of production* (Vol. 6). Springer Science & Business Media.

Fredriksson, P. G., Vollebergh, H. R., & Dijkgraaf, E. (2004). Corruption and energy efficiency in OECD countries: theory and evidence. *Journal of Environmental Economics and management*, *47*(2), 207-231.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society.* Series A (General*)*,120(3), 253-290.

Geller, H., Harrington, P., Rosenfeld, A. H., Tanishima, S., & Unander, F. (2006). Polices for increasing energy efficiency: Thirty years of experience in OECD countries. *Energy policy*, *34*(5), 556-573.

Honma, S., & Hu, J. L. (2008). Total-factor energy efficiency of regions in Japan. *Energy Policy*, *36*(2), 821-833.

Hu, J. L., & Kao, C. H. (2007). Efficient energy-saving targets for APEC economies. *Energy policy*, *35*(1), 373-382.

Hu, J. L., & Wang, S. C. (2006). Total-factor energy efficiency of regions in China. *Energy policy*, *34*(17), 3206-3217.

Lee, C. C., & Chang, C. P. (2008). Energy consumption and economic growth in Asian economies: a more comprehensive analysis using panel data. *Resource and energy Economics*, *30*(1), 50-65.

Mukherjee, K. (2008a). Energy use efficiency in the Indian manufacturing sector: an interstate analysis. *Energy policy*, *36*(2), 662-672.

Mukherjee, K. (2008b). Energy use efficiency in US manufacturing: A nonparametric analysis. *Energy Economics*, *30*(1), 76-96.

Ruggiero, J., & Vitaliano, D. F. (1999). Assessing the efficiency of public schools using data envelopment analysis and frontier regression.*Contemporary Economic Policy*, *17*(3), 321.

Simar, L. and Wilson, P. (2000). Statistical Inference in Nonparametric Frontier Models: The State of the Art. *Journal of Productivity Analysis*, 13(1), 49-78.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management science*, *44*(1), 49-61.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1), 31-64

Song, M. L., Zhang, L. L., Liu, W., & Fisher, R. (2013). Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data. *Applied Energy*, *112*, 1049-1055.

Wei, C., Ni, J., & Shen, M. (2009). Empirical analysis of provincial energy efficiency in China. *China & World Economy*, *17*(5), 88-103.

Zhang, X. P., Cheng, X. M., Yuan, J. H., & Gao, X. J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy*, *39*(2), 644-650.

Zhou, P., & Ang, B. W. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy*, *36*(8), 2911-2916.

Zhou, P., Ang, B. W., & Poh, K. L. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, *189*(1), 1-18.

Zhou, P., Ang, B. W., & Zhou, D. Q. (2012). Measuring economy-wide energy efficiency performance: a parametric frontier approach. *Applied Energy*, *90*(1), 196-200.