Assessment of the optimal rebound effects from energy intensity reduction

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ABSTRACT

Energy efficiency improvement is widely recognized as a cost-effective measure for clean production. In literature, the rebound effects of energy efficiency improvement represented by energy intensity reductions, potential energy savings and actual energy savings are not well defined and properly clarified. To address this issue, this study comprehensively discusses and clarifies how to define and estimate potential and actual energy savings in the assessment. We focus on the well-known concept of rebound effect and propose a new notion of the optimal rebound effect, which avoids the counter-intuitive values in cases of energy intensity increases in neighboring years. The optimal rebound effect must be assessed by an optimization approach, while the traditional rebound effect assumes the observed next-year data as the case of energy intensity reduction. For illustration, a non-radical data envelopment analysis model is used to estimate the potential energy intensity reduction, which serves to assess the optimal rebound effects in four Asian countries including China, India, Japan and Korea, during the period 1973-2017. The findings indicate that neither backfire nor super-conservation appears in the estimated optimal rebound effects.

***Keywords**:* energy policy; energy efficiency; rebound effect; energy savings; carbon emissions

1. Introduction

Energy efficiency improvement is widely taken as a key measure for reducing energy use and carbon emissions, thus contributing to clean production and climate mitigation (IEA, 2018). However, the actual effect of energy use and related carbon emissions may be considerably overestimated, since economic agents are likely to adjust their behavior to increase energy use in response to an energy efficiency improvement (Saunders, 2015; Stern, 2017; Wei and Liu, 2017). This "take-back" effect of economic agents is called "rebound effect" (Khazzoom, 1980; Saunders, 1992). Recent studies on the macroeconomic rebound effect have adopted energy intensity (i.e., energy use per unit economic output) as an indicator of energy efficiency (Jin and Kim, 2019; Shao et al., 2019; Shao et al., 2014; Wei et al., 2019). Some empirical studies have obtained abnormal values of rebound effects, such as extremely high positive (backfire) and negative (super-conservation) values (Shao et al., 2014; Wang et al., 2018; Wei et al., 2019). Jin and Kim (2019) particularly noticed that negative rebound effect can be associated with an increase in energy intensity, which is counter intuitive. Hence, they proposed a new approach for calculation of rebound effects to avoid such abnormal values. With the new approach, the estimated potential energy use was employed to calculate the rebound effects, and a very small value of rebound effects was offered compared with the traditional approach in the literature. In this study, we clarify several issues related to the approach proposed by Jin and Kim (2019) and further propose an alternative approach to avoid the abnormal values by assessing the "optimal" rather than "actual" rebound effect.

From an engineer's perspective, increase in energy efficiency by one percent reduces energy use by one percent for production of one-unit economic output (or energy services). Hence, the potential energy savings in an economy would be proportional to energy efficiency improvement to produce the same economic output. However, the actual energy savings may differ from the expectation due to behavior adjustment of economic agents. For example, energy efficiency improvement means reduced cost in energy, which encourages energy use for more economic output. To quantify the deviations of actual energy savings from the expected potential energy savings, the rebound effect is introduced to measure to what extent the potential energy savings are not realized, which is expressed by "a percentage of the energy efficiency improvement potential, predicted by the engineer" (Berkhout et al., 2000). The rebound effect is further explicitly interpreted as the share in the potential energy savings of the difference between the potential and actual energy savings (Druckman et al., 2011; Haas and Biermayr, 2000). Here while the potential (sometimes also called expected or calculated) energy savings are generally assumed proportional to an energy efficiency improvement, consistent with the perspective of an engineer, the "actual" savings may differ from the observed savings depending on how energy efficiency improvement is defined and estimated by certain modelling and simulation methods. In some studies taking energy intensity as an indicator of energy efficiency, the "actual" energy savings related to technological progress are calculated as the additional energy use to generate only a part of economic growth due to the technological progress (Shao et al., 2019; Shao et al., 2014; Wang et al., 2018) although this is only part of the overall rebound effect as pointed out by Wei et al. (2019).

To empirically assess rebound effect of energy efficiency improvement represented by energy intensity reduction, it is necessary to properly define potential energy savings and actual energy savings. In a recent study, Jin and Kim (2019) proposed to assess the rebound effect by a different approach without calculation of potential energy savings to avoid counter-intuitive values in cases of energy intensity increases. Their values of the rebound effects are dramatically smaller than those in previous studies. In the present study, we discuss and clarify how to properly define and estimate potential and actual energy savings in the assessment. We conclude that it is necessary to identify an alternative "actual" energy use and economic output associated with reduction in energy intensity, which is used to compare potential and actual energy savings for assessment of the "optimal" rather than "actual" rebound effect.

This study contributes in the literature to propose a new notion of the "optimal" rebound effects of energy intensity reduction on energy use and tends to focus on the estimation of potential and actual energy savings. Furthermore, this study also applies a data envelopment analysis (DEA) approach following Jin and Kim (2019) to illustrate how to estimate the optimal rebound effects, providing policy makers with an alternative indicator of rebound effects.

The remainder of the study is organized as follows. Section 2 presents a brief literature review. Section 3 describes methods and data used in this study. Section 4 reports results of a case study involving four Asian countries of China, India, Japan, and Korea from 1973 to 2017 for illustration and Section 5 discusses relevant issues. The last section concludes the study.

2. Literature review

The rebound phenomenon was noticed during the First Industrial Revolution when the coal use was increasing with more energy efficiency technologies in the production as noticed by Jevons (1865). However, it didn't receive serious attention until the 1970s by two economists (Brookes, 1979; Khazzoom, 1980). Since then, the rebound effect has been studied both theoretically (e.g. Lemoine, 2018; Saunders, 1992, 2000; Saunders, 2008; Wei, 2007, 2010; Wei et al., 2019) and empirically (e.g. Anson and Turner, 2009; Saunders, 2013; Shao et al., 2014; Wei and Liu, 2017). Several review articles have summarized the development of the literature over time (A. Greening et al., 2000; Jenkins et al., 2011; Sorrell, 2015; Sorrell et al., 2009). In recent years, energy efficiency improvement has been taken as a key measure to mitigate global warming and several countries such as China and India have set a target on energy efficiency (indicated by energy/emission intensity) in their nationally determined contributions (UNFCCC, 2019).

Energy efficiency improvement can promote economic growth (Chakravarty and Roy, 2016; Chan and Gillingham, 2015; Liu et al., 2019), with the potential to use less energy and generate less energy-related carbon dioxide emissions (Gillingham et al., 2013; Nature, 2013). To what extent energy efficiency improvement can reduce energy use is still a questionable matter, which depends on how energy efficiency and rebound effect is defined (Berkhout et al., 2000), whether the rebound effect is direct, indirect or economy-wide (Greening et al., 2000), and what region is under consideration (Sorrell et al., 2009).

Broadly speaking, energy efficiency can be indicated by energy use per unit economic output in an economy. Since economic output is affected not only by energy use, but also other productive resources such as labor and capital and their efficiency, energy efficiency improvement typically refers to energy savings per unit economic output given constant inputs of other productive resources and their efficiency in energy economics (Gillingham et al., 2013; Saunders, 2008; Wei, 2010). While the rebound effects of energy efficiency improvement such defined provide important insights into understanding of the phenomenon, it suffers several drawbacks such as substitution effects between energy and other resources due to a change in availability of other resources； difficulties to observe and measure such an energy efficiency improvement, and ignored energy savings due to efficiency improvement of other resources than energy, which makes it less appealing to policy makers and other stakeholders (Wei et al., 2019).

On the other hand, although energy intensity, energy use per GDP at the national level, is widely recognized as an indicator for energy efficiency, very few studies of the rebound effects have associated energy efficiency with energy intensity (Jin and Kim, 2019; Shao et al., 2019; Shao et al., 2014; Wei et al., 2019). Among these studies, the overall rebound effect is overlooked and only the part associated with technological changes has been highlighted as pointed out by Wei et al. (2019). Particularly, the approach taking energy intensity for an energy efficiency indicator may lead to counter-intuitive values of rebound effect when the observed energy intensity increases rather than decreases (Wei et al., 2019). To meet the challenge, Jin and Kim (2019) proposed a new approach to estimate the rebound effect in these cases by introducing a new concept of rebound effect, which differs considerably from the widely adopted concept. This study clarifies the differences between the two concepts, and explicitly distinguish the "actual" rebound effect from the "optimal" rebound effect, the latter of which indicates the "best" potential rebound effects.

3. Methods and Data

3.1. Defining the optimal rebound effect from energy intensity reduction

Generally, a rebound effect is associated with the share of un-realized expectation of potential energy savings in total potential energy savings caused by an energy efficiency improvement. If energy intensity is taken as an energy efficiency indicator, a one percent increase in energy efficiency would be expected to reduce energy use by one percent to produce one-unit economic output. However, the energy efficiency improvement can also lead to behavior changes of economic agents so that the economic output may differ from that before the energy efficiency improvement. Certain part of the potential energy savings cannot be realized, rebound effect appears.

As pointed out by Wei et al. (2019) and Jin and Kim (2019), the estimated rebound effects on energy use can be counter-intuitive particularly if energy intensity increases rather than decreases. For example, as shown in Table 2 of Wei et al. (2019) the rebound effects estimated for 40 regions from 1995 to 2009. Super-conservation is obtained for Brazil, Denmark, Luxembourg, and Taiwan, where energy intensity increases in the study period. The super-conservation in these regions does not bring about reduction in energy use. This study illustrates the definition of rebound effect and proposes an approach to assessing the rebound effects from energy intensity reduction.

As described in the introduction section, rebound effect is a concept associated with energy efficiency improvement, namely energy intensity reduction in this study. If energy intensity increases, it makes no sense to calculate the rebound effect (a share in the expected energy savings) as no energy savings could be expected. How could we calculate actual and expected energy savings in such cases if energy intensity is taken an indicator of energy efficiency?

On an annual basis is observed, actual economic output (e.g. GDP) and actual energy use are observed and used to calculate energy intensity of the year. Assume the energy intensity reduces by one percent in the year. For an engineer, the energy use is expected to reduce by one percent to produce the same economic output. Hence, the potential energy savings are one percent of the actual energy use. Then what are the actual energy savings associated with the one percent energy intensity reduction? Since the reduction in energy intensity does not occur and the actual energy use after the reduction in energy intensity cannot be obtained, we face difficulties in calculating the actual energy savings.

If the energy intensity in the next year is lower than this year, the observed energy use and economic output in the next year can be taken an observation of actual results of an reduction in energy intensity of this year, the same as implicitly assumed in some empirical studies (Shao et al., 2019; Shao et al., 2014; Wang et al., 2018). Assume the energy intensity in the next year is reduced by α percent (α>0). The corresponding energy use this year is assumed the same as the observed actual energy use in the next year. Hence, the "actual" energy savings (AES) of this year with the α-percent reduction in energy intensity can be calculated by

$$AES_t = E_{t,actual} - E_{t+1,actual} = EI_{t,actual} \cdot Y_{t,actual} - EI_{t+1,actual} \cdot Y_{t+1,actual} \tag{1}$$

where $E_{t,actual}$, $EI_{t,actual}$, and $Y_{t,actual}$ are the actual energy use, energy intensity, and economic output in the year t, respectively. Correspondingly, the potential energy savings (PES) are α percent of the actual energy use of this year, i.e.

$$PES_t = \alpha\% \cdot E_{t,actual} = \left(1 - \frac{EI_{t+1,actual}}{EI_{t,actual}}\right) \cdot \left(EI_{t,actual} \cdot Y_{t,actual}\right) = \left(EI_{t,actual} - EI_{t+1,actual}\right) \cdot Y_{t,actual} \tag{2}$$

Hence, the rebound effect of this year can be expressed by

$$R_t = \frac{PES_t - AES_t}{PES_t} = \frac{EI_{t+1,actual} \cdot (Y_{t+1,actual} - Y_{t,actual})}{(EI_{t,actual} - EI_{t+1,actual}) \cdot Y_{t,actual}} \quad (3)$$

The calculation seems valid if the energy intensity in the next year is lower than this year. However, the validity of the calculation is problematic if energy intensity rises from this year to the next year. This indicates that the observation of the next year is not plausible to estimate the actual energy savings associated with a reduction in energy intensity. If we can find or estimate another "actual observation" associated with a reduction in energy intensity in a year $\tilde{t}$, the rebound effect of this year can be expressed by

$$R_t = \frac{PES_t - AES_t}{PES_t} = \frac{EI_{\tilde{t},actual} \cdot (Y_{\tilde{t},actual} - Y_{t,actual})}{(EI_{t,actual} - EI_{\tilde{t},actual}) \cdot Y_{t,actual}} \quad (4)$$

Potential energy savings are the difference between the potential energy use and "actual" energy use,

$$PES_t = \left(EI_{t,actual} - EI_{\tilde{t},actual}\right) \cdot Y_{t,actual} \quad (5)$$

"Actual" energy savings are the difference between the actual energy use of this year and the "actual" use in the year associated with a reduction in energy intensity,

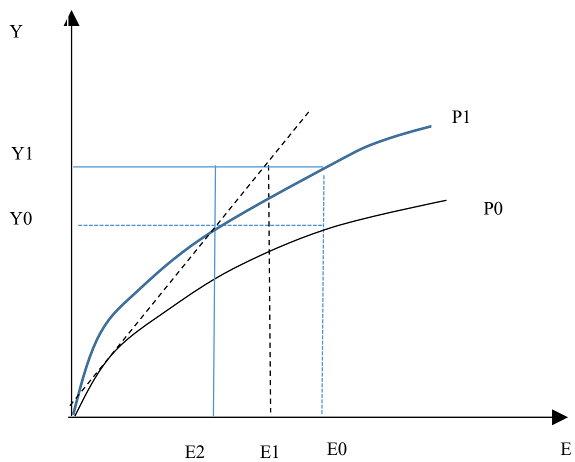
$$AES_t = E_{t,actual} - E_{\tilde{t},actual} = EI_{t,actual} \cdot Y_{t,actual} - EI_{\tilde{t},actual} \cdot Y_{\tilde{t},actual} \quad (6)$$

This approach avoids the estimation of rebound effects based on cases of energy intensity increases while it is still compatible to the standard approach (Wei et al., 2019). The "actual" values of energy use and output associated with an assumed reduction in energy intensity can be derived from a production function where parameters are estimated from observed data like Wei et al. (2019)[1] and Jin and Kim (2019). Since the "actual" energy use and output associated with an energy intensity reduction is estimated rather than observed (e.g. the next year data), it is then important to explicitly present how these data are estimated.

1 The equation below Eq. 1 of Wei, T., Zhou, J., Zhang, H., 2019. Rebound effect of energy intensity reduction on energy consumption. Resources, Conservation and Recycling 144, 233-239.should be $\left|\frac{dE}{E}|_y\right| = -\frac{d\theta}{\theta}$. Energy savings should be positive if energy intensity reduces, which means that expected energy savings should be -$\frac{d\theta}{\theta}$. By contrast, if energy intensity increases, we would expect that we could at least reduce energy use by $\frac{d\theta}{\theta}$. Hence, the expected energy savings should be always positive as $\left|\frac{d\theta}{\theta}\right|$. Actual energy savings are always $\left|\frac{dE}{E}\right|$. In Eq. 2 to calculate rebound in the study, both $\frac{d\theta}{\theta}$ and $\frac{dE}{E}$ take the wrong sign and it happens the result is correct for the case of energy intensity reduction.

We illustrate the alternative approach by Fig. 1 below. In each time, the actual energy use (E0) and actual economic output (Y0) are in the initial production curve (P0). Given the economic output (Y0), a reduction in energy intensity would lead to potential energy savings so that the potential energy use is at the point where the bold production curve (P1) intersects with the horizontal line of Y0. The dashed line from the origin intersecting the bold production curve includes all the points with the same reduced energy intensity. The "actual" energy use and economic output associated with the reduced energy intensity are likely to occur in the point (E1, Y1), i.e., more economic output with certain unrealized expectation of energy savings if other things being equal. In the case of energy intensity increases in neighboring years, the new approach avoids the counter-intuitive values. According to the new approach, super-conservation can only occur with actual reduction in energy use.

Fig. 1. Illustration of the rebound effect of a given reduction in energy intensity.



3.2. Empirical model to estimate the rebound effect

To illustrate the optimal rebound effect proposed in the above section, we adopt the data envelopment analysis (DEA) approach (Tone, 2001) to estimate the "actual" energy use and economic output associated with a reduction in energy intensity. The DEA approach has been used by Jin and Kim (2019), who point out the issue of counter-intuitive rebound effect and proposed a new approach to avoid the issue although their approach is not plausible as argued in Section 5. In principle, the DEA approach allows all inputs and economic output variable for a specific year so that an optimal production combination is identified by assuming the production combinations in all the years of a target period are available for the specific year. In the estimation, we also add a constraint of constant returns to scale, implying the optimal solution cannot be generated from any factors other than the inputs explicitly considered in the estimation. By default, the estimated energy intensity would not be greater than the actual one in a specific year, which avoids any counter-intuitive results associated with energy intensity increases.

For illustration of the DEA approach, we express the idea in mathematical form as follows. The production for a specific year can be expressed by a linear combination of inputs and output, which in our case can be written as

$$Y_t = A + \alpha K_t + \beta L_t + \gamma E_t \quad (7)$$

Where Y is output; K, L, and E are inputs of capital, labor, and energy respectively; $\alpha, \beta,\ and\, \gamma$ are constant parameters; and A is assumed constant and represents all factors other than capital, labor and energy inputs. For a specific year, the optimal production combination can be expressed by a linear combination of the most efficient production years in a target period. For simplicity without the loss of generality, assuming there are two more efficient years than a specific year, a linear combination of the two-year production activities can be expressed by

$$\lambda_{t_1} Y_{t_1} + \lambda_{t_2} Y_{t_2} = A(\lambda_{t_1} + \lambda_{t_2}) + \alpha(\lambda_{t_1} K_{t_1} + \lambda_{t_2} K_{t_2}) + \beta(\lambda_{t_1} L_{t_1} + \lambda_{t_2} L_{t_2}) + \gamma(\lambda_{t_1} E_{t_1} + \lambda_{t_2} E_{t_2}) \quad (8)$$

Where $\lambda_{t_1}\ and\, \lambda_{t_2}$ are positive constants. Since the linear combination is also feasible by default, there must be $\lambda_{t_1} + \lambda_{t_2} = 1$ to follow the assumption of constant A for all years.

In the target period, the DEA approach identifies the production of certain years as the most efficient. These years' production cannot be expressed by a linear combination of the other years' production combination. For these years, we cannot calculate any rebound effects since the DEA approach does not provide an expectation associated with an energy intensity reduction.

Formally, a DEA model evaluates the performance of a set of decision-making units (DMUs), $\{DMU_j : j = 1,2,3, \dots, n\}$. In this study, a DMU refers to the production combination in a year. Each DMU has a set of m inputs measures, $x_{ij}(i = 1,2,3, \dots, m)$and s outputs measures, $y_{rj}(r = 1,2,3, \dots, s)$. According to the combination of inputs and outputs, an optimal production frontier is designed to compare the distance between the real DMU production frontier and a fabricated frontier by using a linear programming model, either radical programming or non-radical programming. Since the slacks-based measure (SBM) model, one non-radical programming DEA model, can deal directly with the input excesses and the output shortfalls, this measure is determined only by consulting the reference-set of the DMU and is not affected by statistics over the whole data set (Tone, 2001). Non-radical programming can better illustrate the distance between the optimal frontier and real production than radical programming. Furthermore, the SBM model relaxes the constraints for both the fixed-link and the free-link cases, enhancing the discriminating power of the model (Lozano, 2015). Hence, a slacks-based DEA model is employed in this study to examine the energy efficiency of Korea during 1973-2012. This method measures not only the energy efficiency, but also takes the slacks of inputs and outputs into consideration. The original non-radical DEA model was proposed by Tone in 2001(Tone, 2001), and was modified by Tone and Tsutsui in 2009, namely the two-stage slack-based measure (SBM) model, which is used in this study to estimate the efficiency of key inputs including energy use of each DMU. Let ρ_k^* denote the estimated efficiency of the kth DMU (DMU_k). Following Tone (Tone, 2001), we have the general SBM model:

$$\rho_k^* = min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_{ik}^-}{x_{ik}}}{1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_{rk}^+}{y_{rk}}} \tag{9}$$

$$s.t. \sum_{j=1}^{n} \lambda_j \boldsymbol{x}_{ij} + \boldsymbol{s}_{ik}^- = \boldsymbol{x}_{ik}, (i = 1,2,3, \dots, m)$$

$$\sum_{j=1}^{n} \lambda_j \boldsymbol{y}_{rj} - \boldsymbol{s}_{rk}^+ = \boldsymbol{y}_{rk}, (r = 1,2,3, \dots, s)$$

$$\lambda_j \geq 0 \ and \ \sum_{j=1}^{n} \lambda_j = 1, \ (j = 1,2,3, \dots, n)$$

$$\boldsymbol{s}_{ik}^-, \boldsymbol{s}_{rk}^+ \geq \boldsymbol{0}, \forall i, r$$

If the optimal solution of the above model is denoted by ($\rho_k^*, s_{ik}^{-*}, s_{rk}^{+*}, \lambda_j^*, \forall i, r, k$), then ρ_k^* demonstrates the estimated efficiency of the DMU_k, s_{ik}^{-*}, s_{rk}^{+*} represents the slacks of inputs and outputs of the measured DMU_k, respectively. When $\rho_k^* = 1$, $s_{ik}^{-*} = s_{rk}^{+*} = 0$, $\forall i, r$, the evaluated DMU is SBM efficient. Note that the energy efficiency can be estimated by the optimal energy use and economic output, which differ from the overall optimal efficiency ρ_k^*. According to Tone (Tone and Tsutsui, 2009), the above SBM function can be transformed into a linear programming problem, which we adopt in this study.

Connecting to Fig. 1, the observed energy use and economic output of each year (DMU) is *E0* and *Y0*, respectively. The optimal energy use and output of DMU projected from the linear programming is the *E1* and *Y1* in Fig. 1, respectively. We then can calculate the rebound effect of the year based on the two points in Fig. 1.

3.3. Data

Annual energy consumption data and macroeconomic data in China, India, Japan and South Korea between 1973 and 2017 are employed in this study since energy consumption data on IEA[2] website are available only in the period. The output data of GDP, input data of labor force and capital are from the website of Penn World Table (PWT)[3], where the data are traced to as early as 1960. In order to make the energy consumption comparable among the four countries, all the GDP and capital are constant 2010 US dollars. Energy intensity is energy consumption divided by GDP. Descriptive statistics of the variables are shown in Table 1. The original data we collected for this study and key results on estimated energy efficiency and rebound effects are provided in an Excel file as the online Supplementary Material.

Table 1 Descriptive Statistics of variables.

	Variable	Obs	Mean	Std. Dev.	Min	Max
China	Labor force (Millions)	45	653	129	394	793
	Capital stock at constant 2011 national prices (in bil. 2011US$)	45	21935	25326	1918	94904
	Energy consumption (Millions of tons of oil equivalent	45	940	518	363	1996
	Real GDP at constant 2011 national prices (in bil. 2011US$)	45	6042	5485	1008	18979
	EI (Millions of toe/ billions in constant 2011 US$)	45	0.22	0.09	0.11	0.41
India	Labor force (Millions)	45	82	24	40	123
	Capital stock at constant 2011 national prices (in bil. 2011US$)	45	5879	4269	885	15847
	Energy consumption (Millions of tons of oil equivalent	45	306	132	143	592
	Real GDP at constant 2011 national prices (in bil. 2011US$)	45	1205	758	267	2950
	EI (Millions of toe/ billions in constant 2011 US$)	45	0.30	0.10	0.20	0.54
	Labor force (Millions)	45	64	4	57	68

2 Data of China, India, Japan and Korea are from the following websites:
https://www.iea.org/sankey/#?c=People's%20Republic%20of%20China&s=Final%20consumption;
https://www.iea.org/sankey/#?c=India&s=Final%20consumption; https://www.iea.org/sankey/#?c=Japan&s=Final%20consumption;
https://www.iea.org/sankey/#?c=Korea&s=Final%20consumption

3 Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt; See: https://www.rug.nl/ggdc/productivity/.

	Capital stock at constant 2011 national prices (in bil. 2011US$)	45	16327	5690	5855	22789
Japan	Energy consumption (Millions of tons of oil equivalent	45	286	39	219	335
	Real GDP at constant 2011 national prices (in bil. 2011US$)	45	3765	993	1927	5020
	EI (Millions of toe/ billions in constant 2011 US$)	45	0.08	0.02	0.06	0.12
	Labor force (Millions)	45	19	5	11	26
	Capital stock at constant 2011 national prices (in bil. 2011US$)	45	3003	2365	252	7527
Korea	Energy consumption (Millions of tons of oil equivalent	45	95	56	18	183
	Real GDP at constant 2011 national prices (in bil. 2011US$)	45	830	572	111	1886
	EI (Millions of toe/ billions in constant 2011 US$)	45	0.12	0.02	0.10	0.16

3. Results

In our non-radical SBM model, each year in each country is set as a DMU and thus the number of DMUs is 45 from 1973 to 2017. Fig. 2 shows the estimated energy efficiency scores. Of all the DMUs, eleven, nine, seventeen and fourteen are efficient in China, India, Japan and Korea respectively. The average efficiency of the four countries ranges from 0.94 to 0.97, among which the highest energy efficiency goes to Japan, followed by China, Korea and India.

The energy use efficiencies in the four Asian countries take similar trends and they are volatile during the period 1973-2017. Among which the fluctuating ranges of Japan are smaller in comparison with the other three countries, varying from the lowest point of 90% in 1999 to 100%. Therefore, Japan is the most efficient in energy use in the four countries. Korea's energy use efficiencies are also quite unstable, ranging from 85.6% to 100% and after 1998, its energy efficiencies keep totteringly climbing up. The energy efficiencies in 1973-2017 in China vary from 85.5% to 100%, while the amplitude of waves gradually become smaller. After 2007, the volatile gap is within 3% and reaches almost full efficiency after 2010. India's energy use efficiencies are quite unstable, and it has the least energy efficient DMUs from 1998-2000, below 85% possibly due to the influence of Asian financial crisis. The number of full efficient years in India is also fewer than other three countries and the averaged level of energy efficiency is only 0.94, much lower than that of other countries. After 2000, Indian energy use efficiencies begin to rise stumblingly.

It is witnessed that all the four countries improved their energy use efficiencies and all the efficiencies use efficiencies climbed up at various speed after 2009. Energy use efficiencies of China, Japan and Korea are toward to fully efficient steadily, while India is a little behind of other three countries and not so steady. The phenomena indicate that countries have paid much attention to the clean production and tried to avoid the environmental protection in recent years.

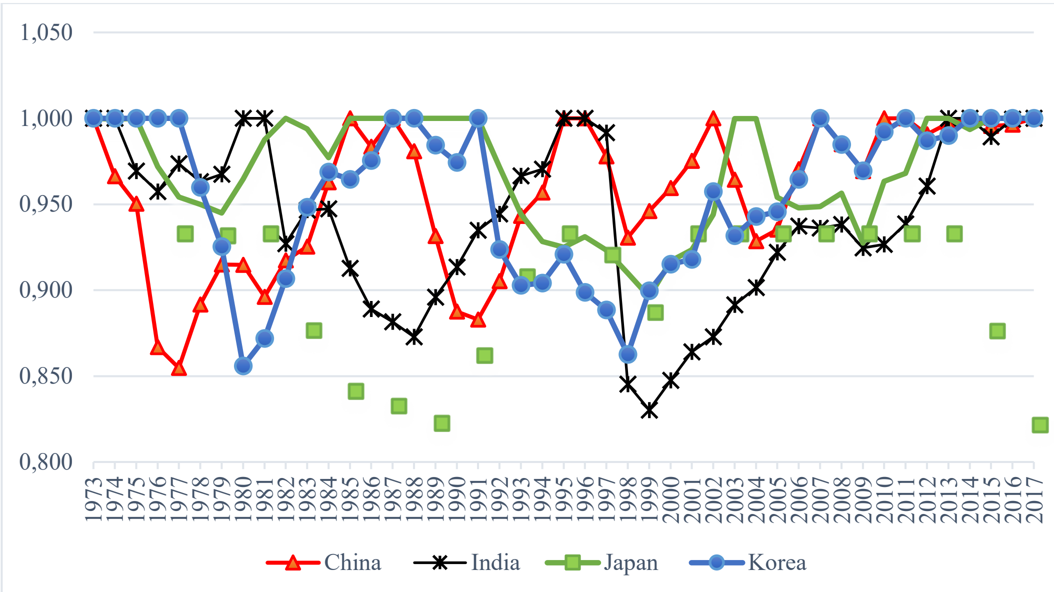


Fig.2. Estimated energy efficiency scores of the four Asian countries

Fig. 3 shows the rebound effects estimated according to the approach proposed in Section 2. When energy use is efficient and GDP is on the production frontier, the reduction in the energy use will lead to the reduction of the output. It is impossible to find a virtual case of a reduction in energy intensity and thus no rebound effect can be estimated. There are fifteen, nine, eleven and fourteen efficient DMUs in China, India, Japan and Korea respectively. When the output is on the production frontier determined by fully efficient use of other resources (either labor or capital), while there is excess input of the energy, the estimated rebound effects are zero, because the energy intensity can be lower through cutting down the surplus input of the energy. While in other years, the rebound effects vary from 1.06% to 100%, due to surplus input of energy and the shortage of output GDP.

The rebound effects of energy use in Japan before 1985 are relatively large compared with the later trend except for some efficient years. The years with the highest rebound effects are just 1993, 1998 and 2009, and the rebound effects are less than 50%. Korea has a trend of rebound effects like Japan. Compared with Japan, Korea's rebound effects surge from 1978 and remain high until 1986. From then on, the rebound effects are declining and stay in the lower level except for the financial crises in 1998 and 2009, possibly because of a series of legislation actions issued to prevent air pollution and protect the environment in 1990s (Kim et al., 1996; Lee and Cho, 2009). The strict legislation actions urge the economy to reduce energy use and improve energy efficiency, leading to comparatively lower rebound effects. The case is different in China. The rebound effects are volatile both before 1982 and after 2009. Before 1982, the rebound effects are stumbling down, while after 2009 the rebound effects totteringly climb up. During the period of 1982-2009, there are almost no rebound effects in China due to rapid economic growth and relatively scarce energy supply. India's rebound effects fluctuate modestly before 1991. After experiencing a short period of no-rebound effects, the rebound effects surge steeply to 100% until 2006, and then quickly fall to the bottom.

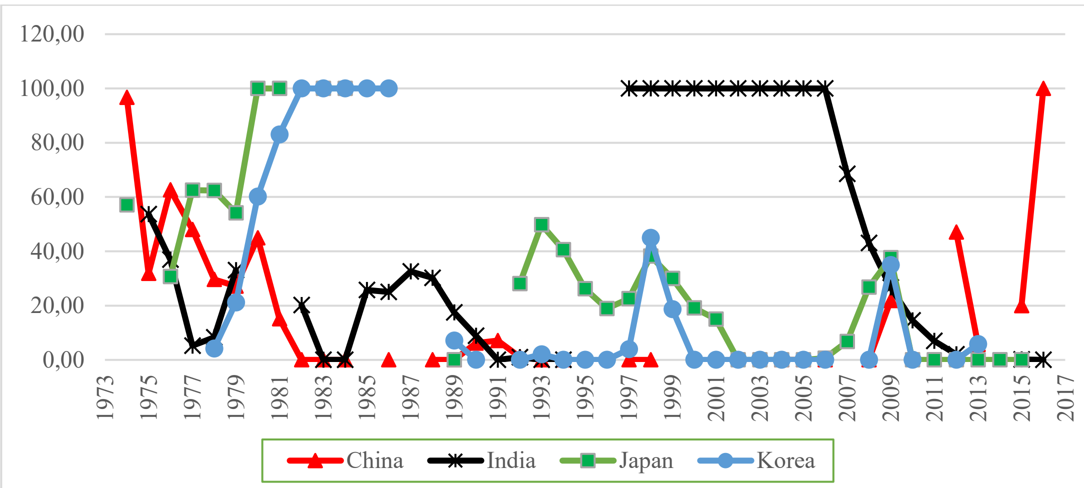


Fig. 3. Rebound effects estimated according to the new approach.

4. Discussion

4.1. Comparison with other approaches

The issue of counter-intuitive values of rebound effects from energy intensity reduction in previous studies (Shao et al., 2014; Wang et al., 2018) has been first discussed by Jin and Kim (2019). They propose a new definition of rebound effect based on potential and actual energy use, i.e.,

$$\tilde{R}_t = \frac{E_{t,actual}}{E_{t,potential}} - 1 \quad (10)$$

Since energy use can be expressed by energy intensity multiplied with economic output, this definition of rebound effect can be rewritten as

$$\tilde{R}_t = \frac{(EI_{t,actual} - EI_{\tilde{t},actual}) \cdot Y_{t,actual}}{EI_{\tilde{t},actual} \cdot Y_{t,actual}} = \frac{PES_t}{E_{t,potential}} \tag{11}$$

This definition differs from the one described in Section 3.1 since it shows the percentage of potential energy savings in potential energy use rather than the amount of potential energy savings. In most cases, potential energy use should be much larger than the potential energy savings. Hence, it is not surprising to obtain much smaller values of the rebound effect as defined by Jin and Kim (2019). However, why the rebound effects need calculating?

The initial purpose of calculating rebound effect is to quantify to what extent the potential energy savings from an engineer's perspective was not materialized in actual economic activities. The prevailing definition of rebound effect is intuitive to show the un-materialized percentage of potential energy savings from a given energy efficiency improvement, where the denominator is the potential energy savings. In the definition proposed by Jin and Kim (2019), it shows the share of un-materialized energy savings in total potential energy use. Without going into detail on how to estimate the potential energy use, it is hard to use such an indicator to explain the rebound effect induced by an energy efficiency improvement. Therefore, we would not compare our results with theirs in this study.

On the other hand, we calculate the yearly rebound effects by following the approach suggested by Wei et al. (2019). As shown in Table 2, almost all the rebound effects are back-fire as a result of an increase in GDP together with a decrease in energy intensity although super-conservation is observed in the cases of either a decrease in both GDP and energy intensity (e.g. Japan and Korea 1997) or an increase in both GDP and energy intensity (e.g. India 2006-2009), where the latter cases are counter-intuitive as the energy efficiency (or energy intensity) was not improved (or reduced) as already pointed out by Jin and Kim (2019). The rebound effects by the traditional approach vary dramatically from year to year since the calculation of the actual energy savings is based on the actual data in the next year, which is affected by many uncontrollable factors such as financial crisis in 1998. In our new DEA approach, the optimal rebound effects vary in the range of 0-100% since they are estimated under strict assumptions of limited inputs of production resources to produce at least the same economic output.

Table 2 Rebound effects by traditional approach suggested by Wei et al. (2019).

Year	China	India	Japan	Korea	Year	China	India	Japan	Korea
1973	-485	160	-212	172	1996	288	735	114	-2459
1974	-290	449	41	212	1997	155	82	-128	-109
1975	45	212	-251	1050	1998	69	-34	8	2083
1976	-248	160	198	-283	1999	153	234	183	867
1977	243	173	192	1172	2000	156	110	26	179
1978	120	225	283	-216	2001	228	754	-7	278
1979	91	120	34	42	2002	-392	170	62	245
1980	111	257	68	107	2003	-167	576	178	119
1981	170	-291	70	94	2004	-539	256	114	160
1982	230	145	213	275	2005	299	233	75	135
1983	245	392	-431	675	2006	254	-2308	89	308
1984	130	307	109	432	2007	212	-919	-20	98
1985	359	334	161	606	2008	239	-119	141	751
1986	263	194	286	366	2009	290	-1213	230	-5161
1987	504	645	946	1536	2010	424	445	-7	334
1988	-170	190	393	-2307	2011	376	122	68	-763
1989	-20	155	258	-104	2012	202	147	117	215
1990	509	169	235	-1950	2013	189	300	12	118
1991	144	154	-155	-95	2014	197	244	54	940
1992	164	123	37	-267	2015	121	227	44	-1226
1993	163	228	-52	984	2016	148	449	337	526
1994	266	176	-252	891					
1995	78	145	200	1013	MEAN	126	121	92	46

Table 3 summarizes the differences between the new proposed method and the traditional methods of estimating rebound effect. The key difference between the two notions of rebound effects is whether the case of a reduction in energy intensity is determined by the actual next-year data or estimated by an optimization approach. Both notions of rebound effects can provide useful information for policy makers. The actual rebound effects alarm the potential large rebound effects (always backfire) in practice while the optimal rebound effects indicate how optimal the rebound effects can be under certain assumptions. A full optimal rebound effect implies that energy use is the bottleneck of the economy while a zero optimal rebound effect indicates that economic output is contained by a bottleneck other than energy and that a reduction in energy intensity results in energy savings alone.

A partial optimal rebound effect corresponds to a situation of modest scarcity of energy use and a reduction in energy intensity has potential to save energy as well as promote economic growth.

Table 3. Differences between the "optimal" and "actual" rebound effect

	"Optimal" rebound in this study	**"Actual" rebound in Wei et al. (2019)**
Data of potential energy intensity	Estimated by an optimization approach such as a DEA model	The actual energy intensity in the next year
Potential energy savings (PES)	Current-year energy use minus optimal energy intensity multiplied by current economic output	Current-year energy use minus the next-year energy intensity multiplied by current economic output
Actual energy savings (AES)	Current-year energy use minus optimal energy use	Current-year energy use minus the next-year energy use
Potential energy intensity is greater than current one?	Impossible for well-designed optimization approaches.	Maybe. Counter-intuitive rebound values are possible.
Backfire (rebound>100%) or super-conservation (rebound<0%)?	Less likely for well-designed optimization approaches.	Commonly observed.
Assessment approach	Optimization approach	Direct calculation based on actual data
Accuracy	Could vary depending on the assumptions and data period used by an optimization approach	Determinant based on actual data.
Usefulness for policy makers	Indicate how optimal the rebound effect could be	Indicate the actual rebound effect.

Notice that if we only aim to avoid the counter-intuitive results in the cases of energy intensity increases by the standard traditional approach, we can simply tell explicitly that the rebound effects for these cases could not be calculated since no reduction in energy intensity is observed. In our opinion, the large rebound effects (e.g. backfire) are not an issue since they just indicate that a reduction in energy intensity is largely induced by economic growth rather than by energy savings, that is, the reduction in energy intensity is not a proper indicator to measure energy savings and carbon dioxide emissions.

4.2. Limitations of the DEA approach

We emphasize that the optimal rebound effects could potentially be estimated by alternative optimization approaches, which might be much better than the DEA approach adopted in this study. One limitation of the DEA approach is that the estimated rebound effects depend overly on the scarcity of energy used in a year as compared with other resources like labor and capital. For example, the relative scarcity of energy use results in full optimal rebound effects (100%) in India from 1997 to 2006.

The rebound value estimated via the DEA approach is valid only marginally. If the energy savings associated with an energy intensity reduction are expected to be so high that energy is no longer scarce in comparison with labor and capital, the case of 100% rebound effect will turn into zero rebound effect since the energy intensity reduction can no longer come from economic growth, indicating that energy gradually becomes less scarce over time and more energy savings will be obtained along with the reduction in energy intensity. Our results show that the transition may take several years. For example, the rebound effect in India goes gradually from 100% in 2006 to nearly zero in 2012. In China, the rebound effect goes gradually from nearly 100% in 1974 to zero in 1982.

The DEA approach assumes that producers can use less resources to produce at least the same economic output as the actual output in a year. The assumption implies that the production cannot use more resources than the actual resources used in a given year, excluding the case of backfire where more energy is used than the actual energy use. In addition, the assumption also implies that estimated energy intensity cannot increase, excluding the appearance of the counter-intuitive cases. In this sense, the estimated results by the DEA approach are optimal solutions subject to available resources in a given year, and thus the estimated rebound effects can be labelled as optimal rebound effects.

The rebound effects estimated via the DEA approach should be interpreted as short-term rebound effects when two features are taken into consideration. One is that the available resources are limited to the actual resources used in a given year. The other feature is that all inputs other than labor, capital and energy are assumed constant, which means the estimated energy efficiency improvement can come only from the available combination of the three resources, excluding the effect of technology improvement over time. For a long-term rebound effect, we should allow more flexible inputs of resources such as capital and labor and technological improvement.

The traditional approach (Shao et al., 2019; Wei et al., 2019) implicitly allows available resources for production to become the values in the next year, relaxing the resource constraint if capital, labor and resource productivities increase over time. The difference in the resource constraint can be one of the key factors to explain the difference between the estimated rebound effects by both approaches, while the other key factor can be that the actual world is not as optimal as assumed by the DEA approach in that the more efficient inputs of resources in the later years might not be available in a given year.

It is worth noting that the DEA approach assumes the potential efficiency gains are based on the actual cases of the years in a target period, always resulting in the most efficient cases for certain years. In our case, 49 of 180 years are identified as the most efficient cases. For these years, we could not estimate rebound effects. While this is understandable, this may also affect the estimation of the rebound effects since a longer period includes more cases, allowing more flexible combination of production and potential changes in estimated rebound effects. In our case of Korea, 9 of the 13 most efficient years appear in either the beginning or the end of the target period 1973-2017. When we choose a shorter period, e.g., 1985-2000, the most efficient years also include the beginning and the closing years of the shortened period. This might be a general conclusion since the efficiency in most years falls within the range from the beginning years to the end years.

5. Conclusions

Realizing the extreme values of rebound effects and meaningless values in the decreasing energy efficiency cases in empirical studies, this study has clarified the reasons and proposed a new notion of the optimal rebound effects, where the calculation of rebound effects in a year are based on the energy intensity and economic output in an "optimal" case of reduced energy intensity for the year. The "optimal" rebound effects differ from the traditional one, which directly uses the actual energy intensity and economic output of the next year to calculate the "actual" rebound effect. A DEA approach is used to illustrate how to calculate the optimal rebound effects for the four Asian countries of China, India, Japan and Korea.

The key issue to estimate the optimal rebound effects is how to define and estimate potential and actual energy savings. Since actual energy use is observable, the key is to define and estimate potential energy use and associated economic output. Based on various assumptions, there are various ways to define and estimate potential energy use and economic output. This study provides one option of a DEA approach for the estimation. The DEA approach estimates the efficiency of energy use based on a target period. The approach always assumes that the most efficient cases are from certain years of the target period and thus the target period has effects on the calculation.

Note that the DEA approach proposed in this study is only one option for the calculation of the optimal rebound effects. Further studies will explore other approaches that can estimate the rebound effects more accurately and reliably. To estimate the optimal rebound effects, the key question is how to estimate the optimal energy use and economic output simultaneously. While the DEA approach could serve this purpose, obvious are its limitations, such as period-depending and linear production function. Better estimation approaches may demand much more data and alternative assumptions. For example, assume that regional producers pursue profit maximization in a specific production functional form, then optimal energy use and economic output can be estimated following the standard economic modeling approach if data of relevant prices are available.

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Glossary of abbreviations

GDP	Gross domestic product
DEA	Data envelopments analysis
AES	Actual energy savings
PES	Potential energy savings
DMU	Decision-making unit
SBM	Slacks-based measure model
PWT	Penn World Table

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