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MEASURING CHINA'S INDUSTRIAL TOTAL-FACTOR ENERGY EFFICIENCY BY A FIXED-EFFECTS TWO-STEP STOCHASTIC METAFRONTIER MODEL

Abstract. *To account for both technology heterogeneity and individual heterogeneity, this paper develops a fixed-effects two-step stochastic metafrontier approach and uses it to evaluate the total-factor energy efficiency of 35 sub-industries in China's industrial sector. The empirical results show that on average the low energy consumption group performs better than the high energy consumption group. However, some sub-industries with high capital intensity in the high energy consumption group perform efficiently in terms of metafrontier energy efficiency, implying that capital embodied technical change is crucial for the improvement of energy efficiency. Moreover, both the high and low energy consumption groups experience a U trend of efficiency performance, implying the government's energy conversation and emission reduction program is effective. In addition, the previous calculations of energy efficiency, ignoring individual heterogeneity, are likely to underestimate the energy efficiency performance.*

Keywords*: Total-factor energy efficiency, technology heterogeneity, individual heterogeneity, stochastic metafrontier approach.*

JEL Classification: L60, O13, Q49.

1. Introduction

China's total final energy consumption has grown rapidly at 8.7% annual rate between 2001 to 2015, from 991.174 million tons of coal equivalent (TCE) in 2001 to 3169.129 million TCE in 2015. It is calculated that, the whole industry consumes 89.5% of the total energy with an upward trend until 2011; the industrial sector accounts for 77.6% of the energy consumption of all industries with a distinct inverted-U trend around 2009 (NBSC, 2018).

Due to its high energy consumption, the industrial sector is always on the top list of Chinese official targets for energy conversation and emission reduction (ECER), e.g., the obligatory reduction goals of energy intensity and carbon intensity in China's 11th, 12th and 13th Five-Year Plan (FYP). To realize the goal of ECER, different industries in the industrial sector should be further assigned

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different and appropriate reduction shares, i.e., energy reduction distribution plan, which relates closely to energy efficiency.

In the total-factor production framework, Hu and Wang (2006) first defined total-factor energy efficiency (TFEE) as the ratio of the target energy input to actual energy input in their proposed data envelopment approach (DEA) model. However, in the model, energy input and other inputs are required to be reduced proportionally, which might lead to the "bucket effect" (Lin and Du., 2013). Mukherjee (2008)and Zhou and Ang (2008)provided different DEA models, keeping the output and non-energy inputs unchanged, to avoid the above problem and reflect the maximum potential of energy conversation. Methodologically, few studies paid attention to the parametric stochastic frontier analysis (SFA) models to evaluate TFEE. In general, traditional DEA models treat the deviation from frontier as inefficiency, while SFA models take it as inefficiency as well as stochastic noises, which is more theoretically appropriate. Despite its advantages, SFA approach has developed much more slowly than DEA approach. Due to the excellent work of Zhou et al. (2012)that utilized the Shephard energy distance function to capture the maximum energy reduction potential, the strand of SFA-TFEE studies has become popular. For example, based on the specification of Shephard energy distance function of energy inefficiency, Honma and Hu (2014) added environmental variables to the SFA model and estimated TFEE scores of Japanese 47 regions during 1996-2008.To deal with individual heterogeneity, Lin and Du (2015)employed the fixed-effects SFA model to estimate total-factor carbon efficiency and Malmquist carbon emissions performance index in China's 30 provinces during the period of 2000-2010.Du and Lin (2017) used the fixed-effects SFA model to estimate the Malmquist energy productivity change of the world's 123 economies from 1990 to 2010.

The underlying assumption of the above studies is that all the decision-making units (DMUs) share a common technology, which might cause biased results due to the presence of inherent differences across groups. Hayami and Ruttan(1970)first introduced the concept of metafrontier to solve the incomparability of production performances for different groups. Battese and Rao (2002)developed stochastic metafrontier function through combining metaproduction and SFA framework, but it had data-generation process (DGP) problems. Battese et al. (2004) proposed a new definition of metafrontier function to solve the DGP problem. They also provided the standard estimation procedure which could be called as two-step approach, i.e., using SFA estimation for group frontiers in the first step and linear (or quadratic) programming computation for the metafrontier in the second step. O'Donnell et al. (2008) further extended it into distance functions and DEA models.

Based on the development of metafrontier function, Lin and Du (2013)used stochastic metafrontier approach (SMFA) to analyze the TFEE of China's 30 regions during 1997 to 2010. Bai et al. (2017)applied the SMFA to measure the environmental performance and potential capacities of carbon

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emission mitigation of 39 Chinese industrial sectors during 2005-2011. All the above studies employed the two-step approach introduced by Battese et al. (2004) and O'Donnell et al. (2008), however, Huang et al. (2014)pointed out that the statistical properties of the metafrontier estimates in the second step were unknown, since the estimation results obtained from programming techniques might be contaminated by random shocks. They instead proposed a new two-step approach that employed SFA in both steps to solve the aforementioned limitation.

This paper aims to evaluate the energy efficiency performance in China's industrial sector, following the parametric SFA strand of literature. We add to the existing literature at two aspects. First, a so-called fixed-effects two-step stochastic metafrontier approach is developed to deal with both individual heterogeneity and technology heterogeneity problems that, to our best knowledge, have not been solved simultaneously in previous studies. Second, there have been many studies investigating TFEE at Chinese region level using parametric techniques (e.g., Zhou et al., 2012; Lin and Du., 2013, 2015; Lai et al., 2016; Jiang et al.,2017), but few studies focus on the industry level. This paper tries to investigate the energy efficiency performance of China's 35 sub-industries.

The rest of this paper is organized as follows. Section 2 introduces the methodology, including the metafrontier framework and estimation method. Then, the empirical results and discussion are presented in Section 3 and 4, respectively. Section 5 concludes the paper.

2. Methodology

2.1 Total-factor energy efficiency with metafrontier

According to the concept of metafrontier, there are two different technologies: one is the group-specific technology that is heterogeneous across different groups; the other is the metafrontier technology (i.e., metatechnology).Suppose a neoclassical production economy, in which capital (K), labor (L) and energy (E) are taken as inputs to produce output (Y). We divide the sub-industries of China's industrial sector into J groups with group-specific technology as:

$$P^j = \{(K^j, L^j, E^j, Y^j) | (K^j, L^j, E^j) \text{can produce } Y^j\}, j = 1,2,\cdots,J \quad (1)$$

Accordingly, the metatechnology is given by

$$P^* = \{(K, L, E, Y) | (K, L, E) \text{can produce } Y\} \quad (2)$$

where P^j and P^* denote group-specific technology and metatechnology, respectively.

Referring to Zhou et al. (2012), the Shephard energy distance functions relative to the group-specific technology and metatechnology are defined as follows:

$$D_E^j(K^j, L^j, E^j, Y^j) = \sup\{\rho | (K^j, L^j, E^j/\rho, Y^j) \in P^j\}, j = 1,2,\cdots,J \quad (3)$$

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$$D_E^*(K,L,E,Y)=\sup\{\rho|(K,L,E/\rho,Y)\in P^*\} \tag{4}$$

In Equations (3) and (4), ρ reflects the maximum potential of energy conversation when keeping the rest input-output variables unchanged. Thus, the groupfrontier energy efficiency (GEE) and metafrontier energy efficiency (MEE) can be described as:

$$GEE=1/D_E^j(K,L,E,Y), MEE=1/D_E^*(K,L,E,Y) \tag{5}$$

Since metafrontier is an envelopment curve of all the groupfrontiers(Battese et al., 2004), the following expression can be directly derived.

$$D_E^*(K,L,E,Y)\geq D_E^j(K,L,E,Y), MEE\leq GEE \tag{6}$$

Battese and Rao (2002) constructed technology gap ratio (TGR) to capture the potential access from groupfrontier to metafrontier. However, O'Donnell et al. (2008) pointed out that an increase in TGR implies a decrease in the gap between groupfrontier and metafrontier, that is, TGR is a negative index. To avoid confusion, they instead introduced a metatechnology ratio (MTR) as follows:

$$MTR=\frac{D_E^j(K,L,E,Y)}{D_E^*(K,L,E,Y)}=\frac{MEE}{GEE} \tag{7}$$

Therefore, MEE can be regarded as:

$$MEE=GEE\times MTR \tag{8}$$

2.2. Model Specification and Estimation

According to the two-step procedure introduced by Battese et al. (2004) and O'Donnell et al. (2008), the first step is to estimate the GEE through SFA and the second step is to calculate MTR by mathematical programming techniques. However, Huang et al.(2014) pointed that the above approach might have some limitations and proposed a new two-step stochastic metafrontier approach, in which SFA is also utilized in the second step. On the other hand, in order to deal with unobserved individual heterogeneity, different fixed-effects SFA models are introduced by Greene (2005) and Chen et al. (2014), etc.

To account for both individual heterogeneity as well as technology heterogeneity simultaneously, we develop a so-called fixed-effects two-step stochastic metafrontier model which is expected to result in more reliable and unbiased TFEE estimates.

In the first step, we utilize a translog function to describe the group specific Shephard energy distance function.

$$\begin{aligned}\ln D_E^{j,t}(\cdot)=&\beta_i^j+\beta_K^j\ln K_t^{ij}+\beta_L^j\ln L_t^{ij}+\beta_E^j\ln E_t^{ij}+\beta_Y^j\ln Y_t^{ij}+\beta_{KK}^j\left(\ln K_t^{ij}\right)^2+\beta_{LL}^j\left(\ln L_t^{ij}\right)^2+\beta_{EE}^j\left(\ln E_t^{ij}\right)^2\\&+\beta_{YY}^j\left(\ln Y_t^{ij}\right)^2+\beta_{KL}^j\ln K_t^{ij}\ln L_t^{ij}+\beta_{KE}^j\ln K_t^{ij}\ln E_t^{ij}+\beta_{KY}^j\ln K_t^{ij}\ln Y_t^{ij}+\beta_{LE}^j\ln L_t^{ij}\ln E_t^{ij}\\&+\beta_{LY}^j\ln L_t^{ij}\ln Y_t^{ij}+\beta_{EY}^j\ln E_t^{ij}\ln Y_t^{ij}+v_t^{ij}\end{aligned} \tag{9}$$

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where $\ln D_E^{j,t}(\cdot) = \ln D_E^{j,t}\left(K_t^i, L_t^i, E_t^i, Y_t^i\right)$, denoting energy inefficiency; v_t^{ij} is a random variable accounting for statistical noises and assumed to bei.i.d $N\left(0, \sigma_{vj}^2\right)$; β_i^j refers to time invariant unobserved individual heterogeneity.

According to Equation (3), the Shephard energy distance function is linearly homogeneous in energy, thus we rewrite Equation (10) as:

$$\ln\left(1/E_t^{ij}\right) = \beta_i^j + \beta_K^j \ln K_t^{ij} + \beta_L^j \ln L_t^{ij} + \beta_Y^j \ln Y_t^{ij} + \beta_{KK}^j\left(\ln K_t^{ij}\right)^2 + \beta_{LL}^j\left(\ln L_t^{ij}\right)^2 + \beta_{YY}^j\left(\ln Y_t^{ij}\right)^2 + \beta_{KL}^j \ln K_t^{ij} \ln L_t^{ij} + \beta_{KY}^j \ln K_t^{ij} \ln Y_t^{ij} + \beta_{LY}^j \ln L_t^{ij} \ln Y_t^{ij} + \varepsilon_t^{ij} \quad (10)$$

where $\varepsilon_t^{ij} = v_t^{ij} - u_t^{ij}$ denotes composite error; $u_t^{ij} = \ln D_E^{j,t}(\cdot) \geq 0$ is assumed to be independent of v_t^{ij} and follows a distribution of $N^+\left(0, \sigma_{uj}^2\right)$. Thus, Equation (10) can be estimated by the fixed-effects SFA techniques.

Greene(2005) introduced a Maximum Likelihood Dummy Variable (MLDV) approach for estimation. The limitation of the MLDV approach is that "incidental parameters problem" may arise when the number of units is relatively large compared to the length of the panel. However, Belotti and Ilardi (2013)showed that the MLDV approach appears to be appropriate when the length of the panel is large enough ($T \geq 10$).

Practically, Equation (10) can be estimated by Maximum Likelihood estimator (MLE) and GEE is predicted by

$$\hat{GEE}_t^i = E\left\{\exp\left(-u_t^{ij}\right) \middle| \hat{\varepsilon}_t^{ij}\right\} \quad (11)$$

The second step is to estimate MTR. We follow the methodology in Huang et al. (2014) to rewrite MTR as follows:

$$MTR_t^i = \frac{E_t^i / D_E^*\left(K^i, L^i, E^i, Y^i\right)}{E_t^i / D_E^j\left(K^i, L^i, E^i, Y^i\right)} = \frac{oE_t^{i*}}{oE_t^{ij}} \leq 1 \quad (12)$$

where E_t^i denotes the actual energy input; oE_t^{i*}, oE_t^{ij} denote the optimal energy input with respect to metafrontier and groupfrontier, respectively. Recall Equation (6), we can easily derive that $MTR_t^i \leq 1$.

Taking natural logarithms in both sides of Equation (12), we obtain:

$$\ln\left(1/oE_t^{ij}\right) = \ln\left(1/oE_t^{i*}\right) - u_t^{ij*} \quad (13)$$

where $-u_t^{ij*} = \ln MTR_t^i \leq 0$, that is, $MTR_t^i = e^{-u_t^{ij*}} \leq 1$.

On the other hand, Equation (10) can be rewritten as:

$$\ln\left(1/E_t^{ij}\right) = \ln\left(1/oE_t^{ij}\right) + \varepsilon_t^{ij} = \ln\left(1/\hat{oE}_t^{ij}\right) + \hat{\varepsilon}_t^{ij} \quad (14)$$

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where $\ln\left(1/oE_t^{ij}\right)$ denotes the deterministic part of stochastic groupfrontier that includes individual heterogeneity; similarly, $\ln\left(1/oE_t^{i*}\right)$ stands for the deterministic part of stochastic metafrontier.

Integrating Equation (13) and Equation (14), we get:

$$\ln\left(1/o\hat{E}_t^{ij}\right) = \ln\left(1/oE_t^{i*}\right) + \varepsilon_t^{ij*} \tag{15}$$

where $\varepsilon_t^{ij*} = v_t^{ij*} - u_t^{ij*}$, $v_t^{ij*} = \varepsilon_t^{ij} - \hat{\varepsilon}_t^{ij}$.

Referring to Huang et al. (2014), u_t^{ij*} can be assumed to be i.i.d $N\left(\mu, \sigma_{uj*}^2\right)$; v_t^{ij*} can be reasonably assumed to be asymptotically normally distributed with zero mean, but may not be independently, identically distributed. In this regard, the quasi-maximum likelihood estimator (QMLE) is applied instead of the standard MLE to get more reliable estimation.

MTR can be predicted by

$$\hat{MTR}_t^i = E\left\{\exp\left(-u_t^{ij*}\right) \middle| \hat{\varepsilon}_t^{ij*}\right\} \tag{16}$$

Finally, MEE can be calculated by estimations of GEE and MTR according to Equation (8).

3. Empirical Analysis

3.1 Data Description

In the sample period of 2001–2015, the National Standard of Industrial Classification has been amended three times. To ensure the consistent statistical coverage of industrial sector, we choose 35 sub-industries that are almost unchanged.

Data of capital stock and labor before 2009 are acquired from Chen (2011) and then are extrapolated following Chen’s methodology; the corresponding raw materials are collected from China Statistical Yearbook and China Industry Economy Statistical Yearbook. Data of energy are measured by final energy consumption and collected from China Energy Statistical Yearbook. Data of value-added are constructed following Chen’s refinement framework; for the missing data after 2007, we apply China’s IO tables (i.e., 2007, 2010 and 2012) and the annual sales revenue to extrapolate. Finally, the nominal data on capital stock and industrial value-added have been deflated into constant price at 1990.

In order to reflect technology heterogeneity, we need to divide sub-industries into different groups. The previous studies, e.g. Li and Lin(2017) and Fan et al.(2015), follow the official economic classification to segment industrial sector into heavy industry and light industry. Even though the differences between heavy industry and light industry are obvious, such classification may not directly reflect the variation of production technologies (concerning energy input).

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Therefore, we construct a simple but practical indicator, i.e., relative energy intensity (REI), to categorize sub-industries.

$$REI_{ij} = \frac{E_{ij}/E_j}{Y_{ij}/Y_j} \tag{17}$$

In Equation (17), E_{ij}/E_j , Y_{ij}/Y_j denote energy input share and value-added share, respectively. Therefore, REI measures the relative degree of energy intensity across sub-industries. That is, if $REI > 1$, this sub-industry is relatively energy-intensive, i.e. high energy consumption industry; if $REI < 1$, the sub-industry is energy-extensive, i.e. low energy consumption industry; if $REI = 1$, the sub-industry equals to the average level of the whole group. According to the average REI of each sub-industry over the period of 2001-2015, the sub-industries can be divided into two groups, i.e., the high energy consumption (HEC) group and the low energy consumption (LEC) group, which are listed in Table 1.

Table 1. The list of code and abbreviation for each sub-industry

Code	Industry	Code	Industry
H01	Coal mining and washing	L19	Textile industry
H02	Oil and natural gas extracting	L20	Textile clothes, shoes and caps
H03	Ferrous metal mining	L21	Leather manufacturing
H04	Non-ferrous metal mining	L22	Timber and wood processing
H05	Non-metal mining	L23	Furniture manufacturing
H06	Paper industry	L24	Printing and intermediary replication
H07	Oil processing, coking	L25	Culture, education and sport activities
H08	Chemical materials and products	L26	Medicines manufacturing
H09	Non-metallic Mineral Products	L27	Chemical fibers manufacturing
H10	Ferrous metal smelting and pressing	L28	Rubber and plastics manufacturing
H11	Non-ferrous metal pressing	L29	Metal products manufacturing
H12	Electricity production	L30	General purpose manufacturing
H13	Gas production	L31	Special purpose manufacturing
H14	Water production	L32	Transport equipment manufacturing
L15	Food processing	L33	Electrical machinery and equipment
L16	Food manufacturing	L34	Communication equipment manufacturing
L17	Beverages manufacturing	L35	Measuring instruments manufacturing
L18	Tobacco manufacturing		

Table 2 shows the statistical summary of selected variables in two groups. Note that the mean values of REI are quite different between HEC group(4.8) and LEC group(0.3). Similarly, energy intensity (E/Y) show significant difference across the above two groups, which supports the classification by REI is appropriate.

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Table 2. Summary statistics and industry classification (at 1990 price)

		HEC group					LEC group				
Var.	Units	Obs.	Mean	Std. dev.	Min	Max	Obs.	Mean	Std. dev.	Min	Max
Y	108 RMB	210	5847.1	8326.1	87.0	43171.0	315	12588.2	20510.4	557.0	154131.0
K	108RMB	210	4365.3	5687.3	256.0	36275.0	315	1711.6	1627.1	48.0	9338.0
L	104 Persons	210	263.6	252.2	17.0	1015.0	315	368.2	256.7	19.0	1082.0
E	104 TCE	210	11026.8	15266.2	351.0	80336.0	315	1595.3	1456.8	88.0	7299.0
E/Y	TCE/104RMB	210	2.9	2.8	0.5	13.6	315	0.2	0.2	0.0	1.2
REI	-	210	4.8	4.9	0.8	25.6	315	0.3	0.2	0.0	1.3

3.2.Estimation Results

Table 3 reports the estimation results for four different frontier functions, the former three of which are estimated by MLE and the last one is estimated by QMLE. Model I (pool) is estimated by pooling all the sub-industries as a whole. Models II and III (HEC and LEC) are estimated within a specific group with reference to Equation (10). We use log-likelihood ratio (LR) to test whether group heterogeneity is statistically significant. That is, $\lambda = -2\{\ln[L(H_0) - L(H_1)]\}$, where ln[L($H_0$)] denotes the log-likelihood value of "pool" regression with the null hypothesis (H_0) that the frontiers of different groups are identical and ln[L(H_1)] denotes the sum of log-likelihood values of both "HEC" and "LEC" regressions with the alternative hypothesis (H_1) that the frontiers of both groups are different. The LR test listed in Table 3 rejects the null hypothesis, indicating that the groupfrontiers are statistically heterogeneous. Model IV shows the QMLE results according to Equation (15) for the second step of the two-step SMFA.

Table 3. Estimated results of different frontier functions

Models	I pool		II HEC		III LEC		IV metafrontier	
Method	MLE		MLE		MLE		QMLE	
Steps	-		First Step				Second Step	
lnK	-0.495***	(0.118)	-2.274***	(0.259)	-0.361*	(0.205)	-0.366*	(0.206)
lnL	-0.843***	(0.293)	1.779***	(0.505)	-0.768*	(0.471)	-0.263	(0.364)
lnY	0.21	(0.162)	0.453*	(0.268)	0.244	(0.229)	-0.208	(0.240)
lnKlnK	-0.039***	(0.01)	0.046**	(0.020)	-0.143***	(0.037)	-0.039***	(0.011)
lnLlnL	0.137***	(0.041)	-0.165***	(0.065)	0.132**	(0.062)	0.095*	(0.053)
lnYlnY	0.080***	(0.019)	0.067**	(0.033)	-0.061	(0.053)	0.091***	(0.030)
lnKlnL	0.153***	(0.032)	0.194***	(0.047)	0.056	(0.063)	0.119***	(0.040)
lnKlnY	-0.001	(0.024)	0.061*	(0.037)	0.236***	(0.081)	0.018	(0.033)
lnLlnY	-0.296***	(0.037)	-0.408***	(0.066)	-0.199***	(0.056)	-0.284***	(0.040)
σ_u	0.109***	(0.015)	0.186***	(0.022)	0.140***	(0.016)	0.113***	(0.014)
σ_v	0.121***	(0.005)	0.077***	(0.011)	0.098***	(0.007)	0.060***	(0.010)
$\gamma=\sigma_u/\sigma_v$	0.902***	(0.018)	2.411***	(0.029)	1.425***	(0.020)	1.880***	(0.010)
Log L	301.592		144.944		223.474		572.413	
LR test	133.652(P-value=0.000)							
Obs.	525		210.000		315		525	

Note: (1) *, **, *** denote coefficient significant at 10%, 5% and 1%, respectively; (2) the figures in brackets are standard deviations.

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All estimated values of the standard deviation of inefficiency (σ_u) and the standard deviation of stochastic noises (σ_v) for models I–IV are significant at the 1%level, implying that the utilization of two-step SMFA is appropriate. In addition, the estimated value of γ is also statistically significant at 1% level; if we create an indicator, i.e., $\gamma^2/\left(1+\gamma^2\right)$, to reflect the ratio of the inefficiency variance (σ_u^2) to the overall variance ($\sigma_u^2+\sigma_v^2$), the values of models I–IV are 0.448, 0.853, 0.670 and 0.779, implying that the influence of stochastic noises can not be ignored.

The first question is whether the difference of technology gap (i.e., MTR) between HEC group and LEC group is statistically significant. In order to answer this question, we apply the Kruskal-Wallis test to examine it. The result shown in Table 4 rejects the null hypothesis that all the samples (groups) are from the same population at 1% level. That is, the HEC and LEC groups are statistically heterogeneous. Moreover, the average MTR of LEC group(0.9306) is higher than HEC group(0.9065), implying that LEC group is closer to the metafrontier.

Table 4 also provides the mean values and standard deviations of GEE and MEE; according to the Kruskal-Wallis test, there are statistically significant differences between HEC group and LEC group. In terms of the average energy efficiency scores, LEC group performs better than HEC group, that is, 0.9131 and 0.8752 for GEE, and 0.8499 and 0.7929 for MEE. The above results indicate that there exist statistically significant differences between groups whether relative to groufrontier or metafrontier.

Table 4. Kruskal-Wallis test for differences between HECS and LECS

	MTR	GEE	MEE
HECS	0.9065	0.8752	0.7929
	(0.0580)	(0.0647)	(0.0732)
LECS	0.9306	0.9131	0.8499
	(0.0160)	(0.0346)	(0.0374)
Kruskal-Wallis test	6.7900	46.0230	97.1530
P-value	0.0092	0.0001	0.0001

Note: the figures in brackets are standard deviations.

Table 5. The GEE of 35 sub-industries in China

Code	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Average
H01	0.919	0.970	0.927	0.753	0.785	0.896	0.889	0.768	0.807	0.924	0.919	0.755	0.773	0.827	0.816	0.848
H02	0.881	0.887	0.852	0.911	0.900	0.926	0.926	0.857	0.935	0.917	0.951	0.954	0.946	0.956	0.962	0.917
H03	0.961	0.956	0.844	0.722	0.684	0.779	0.862	0.859	0.932	0.950	0.879	0.934	0.877	0.885	0.942	0.871
H04	0.970	0.967	0.862	0.789	0.800	0.823	0.881	0.918	0.935	0.940	0.839	0.825	0.810	0.838	0.876	0.872
H05	0.918	0.946	0.809	0.728	0.695	0.710	0.785	0.930	0.923	0.962	0.924	0.892	0.851	0.910	0.938	0.861
H06	0.904	0.897	0.882	0.760	0.874	0.893	0.947	0.831	0.857	0.948	0.921	0.938	0.892	0.909	0.917	0.891
H07	0.927	0.885	0.870	0.801	0.892	0.909	0.904	0.874	0.861	0.930	0.924	0.934	0.876	0.882	0.833	0.887
H08	0.925	0.863	0.796	0.738	0.803	0.845	0.916	0.896	0.941	0.970	0.910	0.935	0.888	0.847	0.804	0.872
H09	0.905	0.847	0.865	0.730	0.830	0.795	0.878	0.891	0.887	0.942	0.835	0.926	0.879	0.936	0.960	0.874
H10	0.979	0.955	0.948	0.903	0.871	0.835	0.812	0.729	0.726	0.804	0.734	0.880	0.859	0.817	0.732	0.839

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H11	0.940	0.866	0.819	0.806	0.877	0.857	0.882	0.922	0.915	0.937	0.918	0.929	0.920	0.917	0.781	0.886
H12	0.952	0.922	0.802	0.882	0.922	0.907	0.891	0.882	0.909	0.900	0.755	0.868	0.875	0.839	0.799	0.874
H13	0.774	0.783	0.889	0.746	0.828	0.877	0.829	0.773	0.884	0.893	0.920	0.936	0.900	0.959	0.956	0.863
H14	0.937	0.947	0.961	0.918	0.925	0.909	0.920	0.893	0.902	0.876	0.872	0.845	0.853	0.852	0.853	0.898
L15	0.893	0.880	0.919	0.868	0.870	0.891	0.909	0.895	0.914	0.945	0.950	0.954	0.884	0.883	0.883	0.902
L16	0.874	0.883	0.931	0.880	0.864	0.875	0.901	0.885	0.904	0.937	0.943	0.949	0.930	0.949	0.957	0.911
L17	0.954	0.939	0.942	0.892	0.893	0.883	0.902	0.884	0.899	0.937	0.937	0.949	0.881	0.914	0.932	0.916
L18	0.947	0.949	0.936	0.945	0.939	0.927	0.913	0.904	0.918	0.935	0.866	0.916	0.908	0.951	0.958	0.927
L19	0.969	0.957	0.944	0.876	0.891	0.874	0.897	0.890	0.904	0.917	0.912	0.917	0.872	0.910	0.908	0.909
L20	0.956	0.950	0.944	0.916	0.909	0.893	0.913	0.919	0.932	0.924	0.921	0.908	0.890	0.920	0.933	0.922
L21	0.944	0.933	0.934	0.916	0.935	0.925	0.934	0.926	0.935	0.944	0.957	0.873	0.846	0.893	0.897	0.919
L22	0.965	0.975	0.961	0.911	0.868	0.867	0.916	0.904	0.891	0.917	0.903	0.908	0.817	0.848	0.896	0.903
L23	0.790	0.915	0.897	0.917	0.933	0.938	0.959	0.938	0.933	0.918	0.939	0.951	0.923	0.788	0.785	0.902
L24	0.913	0.951	0.742	0.785	0.902	0.913	0.928	0.922	0.923	0.906	0.889	0.930	0.939	0.947	0.955	0.903
L25	0.842	0.837	0.907	0.833	0.866	0.880	0.897	0.874	0.880	0.906	0.848	0.967	0.961	0.961	0.967	0.895
L26	0.908	0.922	0.896	0.910	0.909	0.919	0.932	0.921	0.940	0.946	0.944	0.946	0.883	0.912	0.922	0.921
L27	0.880	0.845	0.774	0.948	0.945	0.931	0.910	0.943	0.932	0.947	0.952	0.955	0.919	0.932	0.925	0.916
L28	0.959	0.969	0.959	0.907	0.849	0.868	0.911	0.890	0.904	0.897	0.901	0.873	0.854	0.864	0.884	0.899
L29	0.965	0.956	0.938	0.922	0.918	0.905	0.926	0.936	0.940	0.909	0.924	0.936	0.904	0.921	0.933	0.929
L30	0.946	0.944	0.936	0.928	0.909	0.906	0.925	0.934	0.923	0.925	0.878	0.910	0.921	0.931	0.940	0.924
L31	0.916	0.928	0.914	0.840	0.847	0.853	0.879	0.887	0.901	0.900	0.914	0.946	0.948	0.949	0.963	0.906
L32	0.917	0.903	0.921	0.859	0.916	0.926	0.935	0.922	0.920	0.893	0.885	0.903	0.909	0.934	0.941	0.912
L33	0.970	0.938	0.924	0.890	0.929	0.929	0.923	0.899	0.912	0.906	0.901	0.894	0.873	0.898	0.907	0.913
L34	0.947	0.935	0.914	0.915	0.937	0.934	0.935	0.929	0.925	0.916	0.935	0.932	0.932	0.927	0.919	0.929
L35	0.901	0.874	0.885	0.950	0.948	0.931	0.912	0.917	0.914	0.901	0.942	0.918	0.907	0.933	0.943	0.918
HEC	0.921	0.907	0.866	0.799	0.835	0.854	0.880	0.859	0.887	0.921	0.879	0.896	0.871	0.884	0.869	0.875
LEC	0.922	0.923	0.910	0.896	0.904	0.903	0.917	0.910	0.916	0.920	0.916	0.925	0.900	0.913	0.921	0.913
Whole	0.921	0.916	0.893	0.857	0.876	0.884	0.902	0.890	0.904	0.921	0.901	0.914	0.889	0.901	0.900	0.898

Note: "H" and "L" denote HEC group and LEC group, respectively; the same below.

Table 5 reports the GEE scores of each sub-industry for the period of 2001-2015. As for individual industries, two energy-extensive sub-industries, i.e., communication equipment manufacturing (L34) and metal products manufacturing (L29), perform more efficiently than other sub-industries in the group of LEC; on the contrary, Culture, education and sport activities (L25) is the poorest groupfrontier energy efficiency performance sub-industry in this group. On the other hand, in the group of HEC, Oil and natural gas extracting (H02) has the best efficiency performance, while the ferrous metal smelting and pressing (H10) performs more poorly than other sub-industries.

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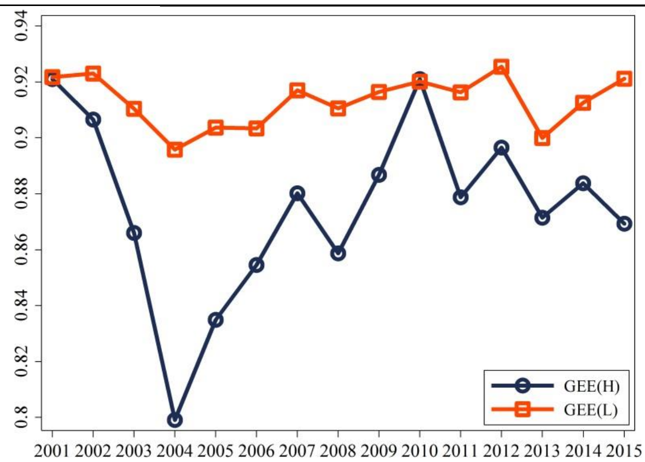

Figure 1. Dynamic trend of GEE in two groups

Figure 1 illustrates the trends of GEE over time. In general, the annual average scores of the energy-extensive group are higher than the energy-intensive group, indicating that industries of LEC group have utilized the existing the group-specific technology more sufficiently than those of HEC group. Note that both HEC and LEC groups have experienced a declining trend before 2004 since China has been ongoing rapid heavy industrialization. Considering that the energy-intensive sub-industries almost belong to heavy industry, the group frontier energy efficiency of HEC group declines even more drastically than LEC group. However, the efficiency deterioration is curbed due to the overcapacity as well as pollution problems. Therefore, both HEC and LEC groups have experienced an increasing trend before 2010 except the year of 2008 when the financial crisis bursts. Since 2010 the HEC group and LEC group perform differently in terms of group frontier energy efficiency; the HEC group shows a declining trend while the LEC group presents a "N" shape.

The result of HEC group may lead to a doubt whether the energy efficiency deteriorates again during the 12th FYP (2011-2015). To answer this question, we need to investigate potential energy efficiency as well.

Table 6. The MTR of 35 sub-industries in China

Code	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Average
H01	0.938	0.930	0.942	0.924	0.833	0.783	0.792	0.884	0.900	0.879	0.913	0.936	0.948	0.977	0.987	0.904
H02	0.949	0.950	0.932	0.920	0.901	0.881	0.883	0.903	0.932	0.921	0.929	0.936	0.947	0.956	0.964	0.927
H03	0.977	0.985	0.983	0.977	0.927	0.866	0.831	0.848	0.881	0.801	0.817	0.816	0.810	0.828	0.885	0.882
H04	0.965	0.968	0.969	0.970	0.968	0.951	0.888	0.865	0.892	0.856	0.878	0.850	0.846	0.843	0.867	0.905
H05	0.914	0.951	0.967	0.970	0.974	0.970	0.964	0.866	0.859	0.834	0.858	0.841	0.836	0.798	0.812	0.894
H06	0.964	0.961	0.961	0.949	0.893	0.867	0.844	0.891	0.880	0.847	0.899	0.911	0.921	0.926	0.934	0.910
H07	0.968	0.967	0.961	0.960	0.934	0.927	0.912	0.936	0.942	0.933	0.925	0.937	0.943	0.945	0.957	0.943
H08	0.978	0.980	0.978	0.973	0.944	0.903	0.833	0.841	0.834	0.790	0.851	0.826	0.824	0.843	0.877	0.885
H09	0.935	0.960	0.956	0.949	0.938	0.953	0.942	0.865	0.879	0.846	0.940	0.922	0.903	0.880	0.901	0.918
H10	0.946	0.968	0.958	0.956	0.918	0.913	0.903	0.931	0.932	0.915	0.933	0.868	0.798	0.833	0.924	0.913

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H11	0.978	0.981	0.978	0.968	0.933	0.907	0.820	0.791	0.823	0.792	0.796	0.785	0.775	0.782	0.811	0.861
H12	0.877	0.887	0.889	0.909	0.883	0.879	0.904	0.924	0.909	0.941	0.974	0.963	0.952	0.973	0.980	0.923
H13	0.813	0.801	0.751	0.838	0.799	0.780	0.801	0.914	0.936	0.958	0.969	0.963	0.969	0.972	0.976	0.883
H14	0.968	0.956	0.951	0.946	0.952	0.946	0.933	0.938	0.938	0.932	0.937	0.935	0.936	0.940	0.936	0.943
L15	0.939	0.947	0.940	0.930	0.931	0.931	0.927	0.934	0.936	0.941	0.943	0.951	0.947	0.946	0.943	0.939
L16	0.940	0.954	0.941	0.929	0.927	0.925	0.919	0.920	0.926	0.935	0.941	0.952	0.952	0.951	0.951	0.938
L17	0.925	0.899	0.904	0.899	0.904	0.904	0.904	0.919	0.928	0.938	0.945	0.950	0.949	0.947	0.948	0.924
L18	0.925	0.910	0.906	0.913	0.924	0.930	0.942	0.950	0.951	0.948	0.943	0.936	0.944	0.945	0.944	0.934
L19	0.947	0.952	0.945	0.938	0.941	0.941	0.932	0.910	0.903	0.916	0.910	0.913	0.892	0.891	0.887	0.921
L20	0.925	0.948	0.943	0.938	0.932	0.932	0.924	0.925	0.925	0.937	0.935	0.951	0.948	0.948	0.948	0.937
L21	0.932	0.947	0.946	0.941	0.941	0.941	0.931	0.921	0.920	0.936	0.940	0.956	0.953	0.953	0.954	0.941
L22	0.915	0.927	0.927	0.919	0.915	0.913	0.916	0.918	0.918	0.928	0.928	0.938	0.935	0.935	0.936	0.925
L23	0.900	0.921	0.922	0.921	0.926	0.930	0.927	0.922	0.917	0.928	0.933	0.939	0.936	0.936	0.939	0.927
L24	0.933	0.951	0.947	0.934	0.917	0.919	0.922	0.913	0.906	0.907	0.909	0.938	0.943	0.944	0.948	0.929
L25	0.909	0.926	0.922	0.917	0.915	0.920	0.912	0.908	0.906	0.920	0.920	0.965	0.971	0.972	0.974	0.931
L26	0.923	0.915	0.909	0.901	0.902	0.903	0.902	0.911	0.919	0.929	0.933	0.940	0.940	0.942	0.943	0.921
L27	0.926	0.915	0.909	0.923	0.936	0.940	0.945	0.946	0.945	0.946	0.946	0.944	0.947	0.944	0.943	0.937
L28	0.949	0.958	0.953	0.948	0.947	0.948	0.945	0.935	0.936	0.948	0.944	0.948	0.941	0.940	0.941	0.945
L29	0.934	0.944	0.931	0.927	0.924	0.924	0.919	0.919	0.916	0.930	0.928	0.943	0.943	0.940	0.945	0.931
L30	0.916	0.939	0.939	0.938	0.939	0.938	0.936	0.931	0.929	0.943	0.943	0.947	0.939	0.939	0.936	0.937
L31	0.916	0.933	0.939	0.931	0.926	0.925	0.921	0.928	0.931	0.945	0.948	0.956	0.954	0.953	0.954	0.937
L32	0.899	0.908	0.909	0.908	0.904	0.909	0.907	0.908	0.911	0.929	0.930	0.936	0.931	0.936	0.933	0.917
L33	0.902	0.919	0.916	0.915	0.921	0.924	0.920	0.910	0.913	0.934	0.937	0.946	0.942	0.943	0.942	0.926
L34	0.887	0.903	0.905	0.908	0.925	0.928	0.931	0.886	0.892	0.935	0.926	0.947	0.948	0.949	0.948	0.921
L35	0.922	0.930	0.933	0.928	0.924	0.924	0.917	0.920	0.920	0.934	0.937	0.935	0.926	0.927	0.927	0.927
HECS	0.941	0.946	0.941	0.944	0.914	0.895	0.875	0.885	0.895	0.875	0.901	0.892	0.886	0.893	0.915	0.907
LECS	0.922	0.931	0.928	0.924	0.925	0.926	0.924	0.921	0.921	0.934	0.934	0.944	0.942	0.942	0.942	0.931
Whole	0.929	0.937	0.933	0.932	0.921	0.914	0.904	0.907	0.911	0.910	0.921	0.923	0.920	0.922	0.931	0.921

The MTR scores of 35 industries from 2001 to 2015 are presented in Table 6. Of the two groups, the MTR score ranges from 0.751 to 0.987 in energy-intensive sector, and 0.886-0.974 in energy-extensive sector. Moreover, in terms of annual average score, the low energy consumption group performs better than high energy consumption sector in maximum, minimum as well as mean value, indicating that the LEC group approaches closer to metafrontier than the HEC group. In other words, the energy-intensive sector needs to improve the economic environment (e.g. establishing higher standard of energy consumption, implementing more stringent environmental regulations) to bridge the technology gap relative to metafrontier.

For individual industries, oil processing and coking (H07) and non-ferrous metal pressing (H11) generally performs best and worst respectively in the group of high energy consumption. It is worth noting that there is little difference between H07 and H11 in terms of GEE, that is, 0.887 and 0.886 respectively. The distinct change of relative status of the two sub-industries just reflects the difference of group-specific technology and metatechnology.

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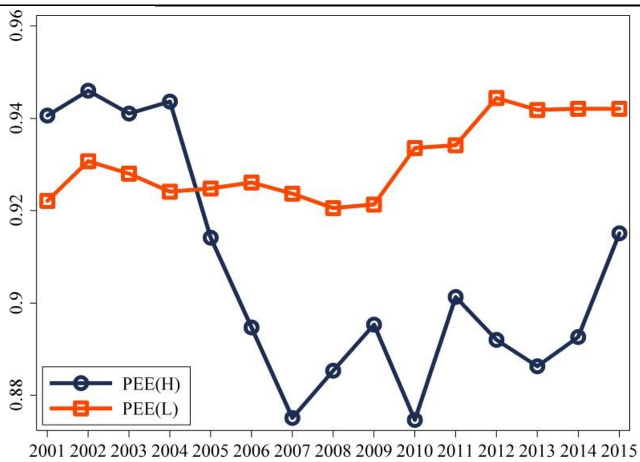

Figure 2.Dynamic trend of MTR in two groups

On the other hand, rubber and plastics manufacturing (L28) and transport equipment manufacturing (L32) are the best and worst MTR performance sub-industry within the group of low energy consumption. It is attractive that L28 performs quite inefficiently in terms of GEE (last but one), however, it obtains the best performance in terms of MTR. This result indicates that L28 is more able to approach the metatechnology based on its own group-specific technology rather than to catch up the efficiency leader within the group; and simultaneously it shows the difference of group-specific technology and metatechnology and further possibilities of efficiency catch-up.

Table 7. The MEE of 35 sub-industries in China

Code	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Average
H01	0.863	0.902	0.873	0.696	0.654	0.701	0.704	0.679	0.726	0.812	0.839	0.706	0.733	0.807	0.805	0.767
H02	0.836	0.842	0.794	0.837	0.811	0.815	0.818	0.774	0.871	0.844	0.884	0.893	0.896	0.914	0.927	0.851
H03	0.939	0.941	0.829	0.705	0.634	0.675	0.716	0.728	0.821	0.761	0.718	0.762	0.710	0.733	0.834	0.767
H04	0.935	0.936	0.835	0.766	0.775	0.783	0.783	0.794	0.834	0.804	0.737	0.702	0.685	0.707	0.760	0.789
H05	0.838	0.900	0.782	0.706	0.677	0.689	0.757	0.805	0.792	0.803	0.793	0.750	0.712	0.726	0.762	0.766
H06	0.872	0.862	0.847	0.721	0.781	0.775	0.799	0.740	0.754	0.803	0.828	0.854	0.822	0.842	0.856	0.810
H07	0.897	0.855	0.837	0.769	0.833	0.843	0.825	0.818	0.811	0.868	0.855	0.875	0.826	0.833	0.797	0.836
H08	0.904	0.846	0.778	0.718	0.758	0.764	0.763	0.753	0.785	0.766	0.774	0.772	0.731	0.714	0.705	0.769
H09	0.846	0.813	0.826	0.693	0.778	0.757	0.828	0.770	0.780	0.797	0.785	0.854	0.794	0.823	0.865	0.801
H10	0.927	0.925	0.907	0.863	0.800	0.762	0.733	0.678	0.677	0.736	0.685	0.764	0.685	0.680	0.676	0.767
H11	0.919	0.850	0.800	0.780	0.818	0.778	0.723	0.729	0.753	0.743	0.731	0.729	0.713	0.717	0.634	0.761
H12	0.835	0.817	0.713	0.802	0.814	0.797	0.805	0.815	0.826	0.846	0.736	0.836	0.833	0.817	0.783	0.805
H13	0.629	0.627	0.668	0.625	0.662	0.685	0.664	0.706	0.827	0.856	0.891	0.901	0.872	0.932	0.933	0.765
H14	0.907	0.905	0.914	0.869	0.881	0.860	0.859	0.838	0.846	0.817	0.817	0.790	0.798	0.801	0.799	0.847
L15	0.839	0.834	0.864	0.807	0.809	0.830	0.843	0.836	0.855	0.889	0.895	0.907	0.837	0.835	0.832	0.847
L16	0.821	0.842	0.876	0.818	0.801	0.809	0.828	0.814	0.837	0.876	0.888	0.904	0.885	0.902	0.909	0.854
L17	0.883	0.844	0.852	0.802	0.807	0.799	0.815	0.813	0.834	0.878	0.886	0.902	0.835	0.866	0.883	0.847
L18	0.876	0.863	0.848	0.863	0.868	0.862	0.860	0.859	0.873	0.886	0.817	0.858	0.857	0.899	0.904	0.866
L19	0.918	0.911	0.892	0.822	0.838	0.823	0.836	0.810	0.816	0.840	0.830	0.837	0.778	0.810	0.805	0.838
L20	0.884	0.900	0.890	0.859	0.847	0.832	0.844	0.851	0.861	0.865	0.861	0.863	0.843	0.872	0.884	0.864

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L21	0.880	0.884	0.884	0.862	0.880	0.870	0.869	0.852	0.860	0.883	0.900	0.835	0.806	0.851	0.855	0.865
L22	0.882	0.904	0.891	0.837	0.794	0.791	0.839	0.830	0.818	0.852	0.838	0.852	0.764	0.793	0.838	0.835
L23	0.711	0.843	0.827	0.845	0.863	0.872	0.890	0.865	0.856	0.853	0.876	0.893	0.864	0.738	0.737	0.836
L24	0.852	0.905	0.702	0.733	0.827	0.839	0.855	0.842	0.836	0.822	0.808	0.872	0.886	0.894	0.905	0.839
L25	0.765	0.775	0.837	0.764	0.792	0.810	0.818	0.794	0.798	0.834	0.780	0.934	0.933	0.935	0.942	0.834
L26	0.838	0.843	0.815	0.820	0.819	0.829	0.840	0.840	0.864	0.878	0.881	0.890	0.830	0.859	0.870	0.848
L27	0.816	0.773	0.703	0.875	0.885	0.876	0.860	0.892	0.880	0.895	0.900	0.901	0.870	0.880	0.872	0.858
L28	0.910	0.928	0.915	0.860	0.804	0.823	0.861	0.832	0.846	0.850	0.851	0.827	0.804	0.813	0.832	0.850
L29	0.901	0.903	0.873	0.855	0.849	0.836	0.851	0.861	0.861	0.845	0.857	0.882	0.853	0.866	0.882	0.865
L30	0.866	0.887	0.879	0.870	0.854	0.850	0.865	0.869	0.857	0.872	0.828	0.862	0.865	0.874	0.880	0.865
L31	0.839	0.865	0.859	0.783	0.784	0.789	0.809	0.824	0.839	0.850	0.866	0.905	0.904	0.905	0.919	0.849
L32	0.824	0.820	0.837	0.780	0.827	0.841	0.849	0.837	0.838	0.830	0.823	0.845	0.846	0.875	0.878	0.837
L33	0.874	0.862	0.847	0.814	0.855	0.858	0.849	0.818	0.833	0.847	0.845	0.846	0.822	0.846	0.855	0.845
L34	0.840	0.844	0.827	0.830	0.867	0.867	0.871	0.823	0.825	0.857	0.867	0.882	0.883	0.880	0.871	0.856
L35	0.830	0.812	0.826	0.882	0.876	0.860	0.836	0.844	0.841	0.842	0.883	0.858	0.840	0.865	0.874	0.851
HECS	0.868	0.859	0.815	0.754	0.763	0.763	0.770	0.759	0.793	0.804	0.791	0.799	0.772	0.789	0.795	0.793
LECS	0.850	0.859	0.845	0.828	0.836	0.836	0.847	0.838	0.844	0.859	0.856	0.874	0.848	0.860	0.868	0.850
Whole	0.857	0.859	0.833	0.798	0.806	0.807	0.816	0.807	0.824	0.837	0.830	0.844	0.818	0.832	0.839	0.827

It is worth noting that the scores of GEE relative to different groupfrontier scan not be directly compared with each other since the group-specific technologies are heterogeneous. On the contrary, the scores of MTR of different groups are comparative, however, they correspond to the artificial DMUs rather than actual ones. In order to assess the comparative energy efficiency performance relative to the actual DMUs, we further calculate the MEE scores which are presented in Table 7.

We can see that the efficiency scores are on average higher than that in Shen and Lin (2017), which may be partly due to the isolation of the individual heterogeneity from the inefficiency term through our fixed effects specification. Moreover, the MEE scores of each industry are systematically lower than the GEE scores shown in Table 5, revealing the technology gaps between groupfrontiers and metafrontier. In terms of MEE, the LEC group in general performs better than HEC group, like the case of MTR.

For individual industries, tobacco manufacturing (L18) performs most efficiently across sub-industries within LEC group as well as the whole industrial sector. On the contrary, non-ferrous metal pressing (H11) has the poorest MEE performance. It is worth noting that the best and worst MEE performance sub-industries are different from those in terms of GEE, implying the presence of technology heterogeneity.

Figure 3 presents the annual average scores of MEE and the pooled energy efficiency calculated from the estimation results of model I in Table 3. As may be observed, the MEE scores of LEC group is higher than the HEC group except 2001. Moreover, the changing curves of the two groups resemble each other except the period of 2001-2002. In general, the MEE performance in both groups has undergone a distinct decline during the period of 2001-2004 due to the rapid heavy industrialization. From then on, both groups have experienced an increase until around the beginning of the 12th FYP period. However, after a short decline, the

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MEE in both groups starts to increase again. Recall Figure 1 that shows a general decline of GEE in HEC group during the 12th FYP period (2011-2015), we now find that from the point of metafrontier the HEC group has experienced a U-shaped change. These results imply that China's ECER program seems to take effect, albeit it seems more effective in 11th FYP period than 12th FYP period.

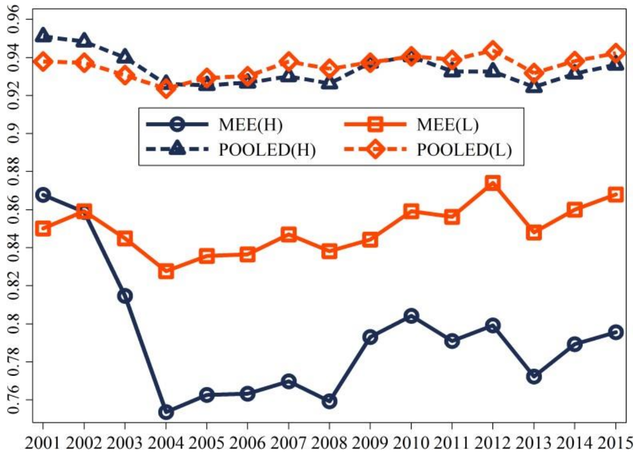

Figure 3. Comparison of dynamic metafrontier and pooled energy efficiency in two groups

Comparatively, the pooled energy efficiency tends to overstate the efficiency level of both HEC and LEC groups and narrow gaps between groups, implying that the assumption of homogeneous technology is somewhat inappropriate and biased. In addition, combined with Figure 1 and Figure 2, we can see that the HEC group performs more poorly than the LEC group in terms of GEE, MTR and MEE, indicating that the HEC group should strengthen its ability in the utilization of group-specific technology as well as metatechnology.

4. Discussion of MEE and REI

The empirical results in 3.3 seem to show that the low energy consumption group performs better than high energy consumption group in terms of energy efficiency. So whether is it the same case at sub-industry level?

Table 8. Comparison of MEE and REI of 35 sub-industries in China

	MEE			REI		
code	Mean	Std.dev	Rank	Mean	Std.dev	Rank[a]
H01	0.767	0.080	31	4.609	0.902	31
H02	0.851	0.045	10	18.527	4.277	35
H03	0.767	0.090	30	2.152	0.463	25
H04	0.789	0.074	28	1.544	0.461	24
H05	0.766	0.060	33	1.120	0.222	22

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H06	0.810	0.029	25	1.193	0.052	23
H07	0.836	0.021	21	8.520	1.668	33
H08	0.769	0.040	29	2.503	0.174	28
H09	0.801	0.058	27	2.961	0.390	30
H10	0.767	0.058	32	6.045	0.898	32
H11	0.761	0.067	35	2.352	0.230	27
H12	0.805	0.017	26	2.901	0.563	29
H13	0.765	0.022	34	2.342	0.911	26
H14	0.847	0.022	15	9.838	2.778	34
L15	0.847	0.047	14	0.434	0.036	16
L16	0.854	0.032	8	0.548	0.055	19
L17	0.847	0.051	16	0.412	0.041	15
L18	0.866	0.044	1	0.147	0.026	5
L19	0.838	0.096	19	0.662	0.080	20
L20	0.864	0.067	5	0.198	0.018	8
L21	0.865	0.037	4	0.205	0.025	9
L22	0.835	0.123	23	0.301	0.051	13
L23	0.836	0.043	22	0.130	0.033	4
L24	0.839	0.039	18	0.271	0.050	11
L25	0.834	0.035	24	0.156	0.045	6
L26	0.848	0.019	13	0.292	0.033	12
L27	0.858	0.023	6	0.753	0.266	21
L28	0.850	0.039	11	0.445	0.078	17
L29	0.865	0.024	3	0.474	0.050	18
L30	0.865	0.055	2	0.334	0.024	14
L31	0.849	0.039	12	0.249	0.038	10
L32	0.837	0.020	20	0.190	0.035	7
L33	0.845	0.014	17	0.118	0.010	3
L34	0.856	0.046	7	0.048	0.003	1
L35	0.851	0.023	9	0.109	0.021	2

Note: the superscript of “a” denotes the ranks of REI scores from small to big in order to adhere to the ranks of MEE.

Table 8 shows the comparison of MEE and REI in terms of ranks of each sub-industry. First, the best three sub-industries of metafrontier energy efficiency, *i.e.*, L18 (1), L30 (2) and L29 (3), ranks 5th, 14th and 18th, respectively of relative energy intensity. On the other hand, the poorest three sub-industries of MEE, *i.e.*, H11 (35), H13 (34) and H05 (33), correspond to number 27, number 26 and number 22 respectively of REI. The above results indicate that even though the best and poorest efficiency sub-industries indeed belong to the LEC group and the HEC group respectively, their ranks have distinctly changed, implying the difference between REI and MEE, or the difference between partial-factor energy efficiency and total-factor energy efficiency.

Moreover, we can observe that all the sub-industries of the HEC group are at the bottom of the MEE list except H02, H14 and H07, which ranks 10th, 15th and 21st respectively. So what is the underlying reason?

To explore it, we here test the influence of capital in the HEC group. Capital, in general, has two different influencing mechanism of energy efficiency.

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First, it can lead to more energy consumption relative to the output due to the complementarity between capital and energy, and thus lowers the corresponding energy efficiency. Second, it can also reduce energy consumption due to its embodied technology that exists in machine and equipment widely.

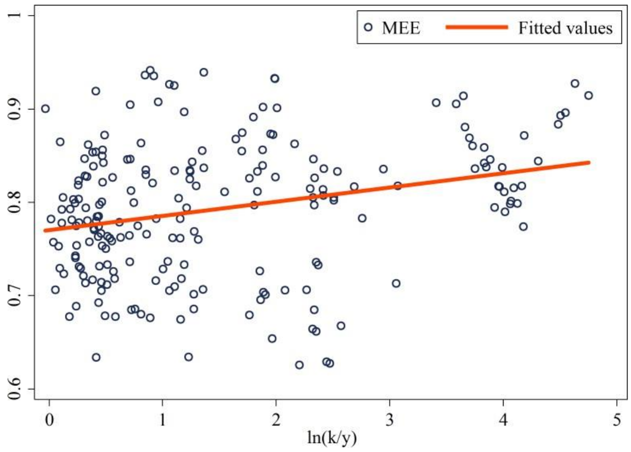

Figure 4.Correlation between MEE and capital intensity in HEC group

Figure 4 illustrates the correlation between MEE and capital intensity (denoted by ln(k/y)) in the HEC group. It can be observed that MEE and capital intensity are positively correlated in the HEC group, implying that the effect of embodied technology is dominant in the HEC group. Meanwhile, we find that H02, H14 and H07 stay at high level of capital intensity; especially, the former two sub-industries keep at the top of the list. That is, it is capital embodied technology that improve the energy efficiency of the high energy consumption sub-industries, implying that the adoption of advanced capital goods may be an effective measure for energy conversation and emission reduction program.

5. Conclusions

In this paper, a fixed-effects two-step stochastic metafrontier model is developed to deal with individual heterogeneity and technology heterogeneity simultaneously. The model is then used to evaluate the energy efficiency performance of 35 sub-industries in China's industrial sector for the period of 2001-2015, and the main empirical results are shown as follows.

First, the average score of metafrontier energy efficiency from 2001 to 2015 is 0.827, which is relatively higher than the previous studies (e.g., Shen and Lin, 2017) due to the isolation of individual heterogeneity from the inefficiency term in our approach. Second, the LEC group performs better than HEC group no matter relative to groupfrontier or metafrontier, indicating that the HEC group should utilize both group-specific technology and metatechnology more efficiently. Third, some sub-industries with bad REI ranks but good capital intensity ranks in the HEC group perform efficiently in terms of MEE, implying that capital

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embodied technical change is very important for the improvement of energy efficiency. Forth, in view of MEE, both the LEC and HEC groups become more energy efficient since around 11th FYP period (2006-2010), albeit it seems more effective in 11th FYP period than in 12th FYP period, implying that China's ECER program is effective.

These results suggest that, to perfectly fulfil the ECER targets, the Chinese government need to formulate heterogeneous energy policies for high and low energy consumption industries. Specially, the Chinese government should encourage the energy-intensive industries to pay more attention to the sufficient utilization of the existing group-specific technology and promote the technology diffusion and spillover cross different groups. In addition, investment on capital goods, embodied new and energy conversation technology, may be a good choice when China is now ongoing rapid industrialization and urbanization.

Finally, there are several possible directions for future research. For example, undesirable outputs could be incorporated into the present framework to capture environmental effect. In addition, this framework has investigated the static performance of energy efficiency, which could be extended into dynamic framework to explore the driving forces of the growth of metafrontier energy efficiency in the future.

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