RESEARCH ARTICLE

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Energy rebound effect in China's manufacturing sector: Fresh evidence from firm-level data

Abstract   The rebound effect refers to the phenomenon that individuals tend to consume more energy in the face of energy efficiency improvement, which reduces the expected energy-saving effect. Previous empirical studies on the rebound effect of regions and sectors do not provide microscopic evidence. To fill this gap, we use China's firm-level data to estimate the rebound effect in China's manufacturing subsectors, providing a detailed picture of China's rebound effect across different sectors and different regions in 2001–2008. Results show that a partial rebound effect robustly appears in all industries, and the disparity between sectors is quite broad, ranging from 43.2% to 96.8%. As for the dynamic rebound effect of subsectors, most subsectors present an upward trend, whereas few subsectors show a clear downward trend. As a whole, the declined trend of the rebound effect is driven by the descent of minority sectors with high energy consumption and high energy-saving potential. In addition, we find that the disparity of the rebound effect across sectors is more significant than that across regions.

Keywords   energy rebound effect, energy efficiency, manufacturing sector, firm-level data, China

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1   Introduction

Since the end of the last century, China has demonstrated an astonishing rate of economic development. On the road to industrialization, China's energy consumption is characterized by substantial total consumption and a continuing trend of growth in demand (as shown in Fig. 1). China statistically has the largest share (about 26.1%) of primary energy consumption worldwide in 2020, along with an upward consumption trend even amid the damages of the COVID-19 pandemic (BP, 2021). Given its scale and foreseeable growth, China's energy consumption is a necessary topic. Meanwhile, air pollution and environmental deterioration are always accompanied by massive energy consumption (Zhang et al., 2019). Thus, under economic downturn and environmental degradation pressure, China has proposed energy consumption reduction tasks to seek sustainable development (Liu et al., 2016). Policies have been conducted since the 11th Five-year Plan (a phased economic development program from 2006 to 2010 led by the Chinese government), such as the Top-1000 Energy-Consuming Enterprises program[1] and the Ten Key Energy-Saving Projects[2] (Yu et al., 2015). On the one hand, large enterprises are promoted to reduce energy consumption. On the other hand, small- and

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[1] To implement the 11th Five-year Plan, the government issued the Notice of the State Council on the Recent Key Work of Building an Energy-saving Society, requiring strengthening the energy conservation management in key energy-consuming enterprises. A campaign to save energy was launched in a thousand enterprises in nine key energy-consuming industries, including iron and steel, non-ferrous metals, coal, electric power, petroleum and petrochemical, chemical, building materials, textile, and papermaking.

[2] The Ten Key Energy-Saving Projects cover a wide range of potential energy-saving areas, including industry as an important component.
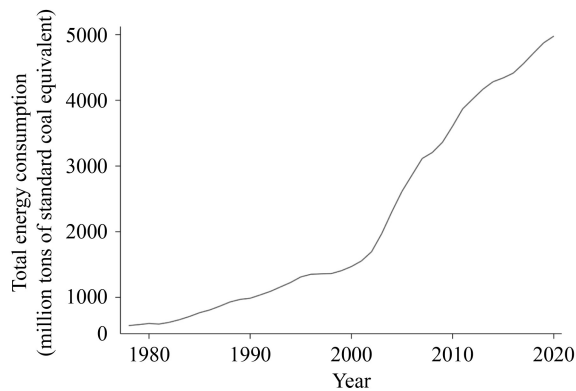
Fig. 1 Energy consumption in China (Note: The data are from China's National Bureau of Statistics).

medium-sized enterprises' outdated production capacity is eliminated (Li et al., 2019b). With the benefit of these top–down policies, energy efficiency improvement is in view.

Do these policies actually achieve their anticipatory energy-saving goals? Theoretically, the increase in energy efficiency allows a product unit to consume less energy (Patterson, 1996). In reality, however, we observe that energy efficiency and energy consumption are not reversed at the same rate (Khazzoom, 1980; Zhang et al., 2017). Many empirical studies have also supplemented that the realization of the energy-saving policies is discounted (Zhang and Lin Lawell, 2017; Zhang et al., 2017; Yan et al., 2019). These pieces of evidence imply that when looking at the energy-saving effect of efficiency improvement, we also need to consider the behavioral response to energy efficiency improvement, that is, the rebound effect.

Discussion on the rebound effect stems from the famous Jevons paradox. Jevons (1865) discussed that technical improvements in engines had accelerated coal consumption. For broader themes, the rebound effect is promoted as the lower-than-expected energy savings brought about by energy efficiency improvements, and sometimes even increased energy consumption than before (Saunders, 2013). Saunders (2008) theoretically deduced two mechanisms of the rebound effect. One is the strength/substitution effect. Improved energy efficiency reduces the actual unit price of energy services, and energy becomes cheaper relative to other inputs. Therefore, more energy is invested in production to replace other inputs. The other is the output/income effect. The progress of the total factor productivity saves costs, and this part of the resources can be used to expand production and increase energy demand. Zhang and Lin Lawell (2017) estimated the two effects separately in the context of China. Under various spatial and temporal scales, they could not monitor the existence of the output/income mechanism. Liu et al. (2019) modeled the aggregate rebound effect, which is the sum of the substitution and output effects, with magnitudes of 37.0%, 13.1%, and 23.9%, respectively, based on production theory and cost function.

Economists generally acknowledge the existence of the energy rebound effect, but its magnitude remains controversial (Zhang and Lin Lawell, 2017). Previous studies have provided plenty of evidence on the rebound effect in different countries (Saunders, 2013; Adetutu et al., 2016). In the context of studies on China, Li and Lin (2015) showed heterogeneous estimation results, ranging widely from 1.11% to 147.97% across China's 21 sectors. Analyses of transportation and time series were also applied to China's scenario (Lin and Liu, 2012; Wang and Lu, 2014). Researchers have also contributed to exploring the rebound effect in the residential sector. We summarize the typical studies in Table 1.

The most relevant to this study correlates with the rebound effect evaluation of China's industrial sector. Li

Table 1 Related literature about the rebound effect in the residential sector

Reference	Subsector	Time period	Region	Method	Rebound effect estimates
Du et al. (2021a)	Urban residents	2001–2014	30 Chinese provinces/cities	Stochastic energy demand frontier model	65.4% on average
Zha et al. (2022)	Urban households	2002–2017	30 Chinese provinces/cities	Environmentally extended multiregional input–output model, price elasticity model, and re-spending model	The direct carbon rebound effect is 50%, and the indirect rebound effect will be lower than 20%
Wang et al. (2019)	Residents	/	/	Consumer expenditure reallocation with cumulative energy consumption through integrating a re-spending framework and an input–output analysis under different scenarios	/
Chen et al. (2022)	Urban households	2002–2017	30 Chinese provinces/cities	An elasticity approach with an individual fixed-effect variable coefficient panel data model	59.9% on average
Zhao and Li (2020)	Residential electricity use	2010–2016	30 Chinese provinces/cities	Panel data model and panel threshold model	84.94%
Lin and Zhu (2021)	Household electricity consumption	2010–2018	25 Chinese provinces/cities	Stochastic energy demand frontier model	48.0% on average
Du et al. (2021b)	Residential buildings	1994–2016	China's urban and rural areas	Linear approximation of the almost ideal demand system model	79.4%–110.0% in urban areas and 115.3%–120.4% in rural areas

et al. (2016) used an output distance function approach on industrial sectors with a rebound effect estimation of around 88.4%. They argued that this relatively high result was reasonable because the evaluation target was the production side instead of the energy end-use sectors. Zhang et al. (2017) reckoned an average effect of 39.0% in China's industrial sectors and 28.0% in China's manufacturing sector with the same decreasing trend. Ouyang et al. (2018) found that the industrial sectors' rebound effect for 14 cities in the Yangtze River Delta is approximately 40.0%. By classifying heavy and light industries, similar estimates were conducted again, and the rebound effect was estimated at 74.3% and 37.7% in the studies of Lin and Li (2014) and Lin and Tian (2016), respectively. Liu et al. (2019) decomposed the energy rebound effect into the substitution and output effects. They found that the rebound effect for the aggregate, heavy, and light industries were 37.0%, 32.3%, and 100.8%, respectively. In a more specific classification of the light industry, Lin and Xie (2015) investigated the rebound effect for the food industry and regarded the magnitude as 34.4% during 1980–2012. These studies have suggested that the magnitude of the rebound effect remains uncertain. In summary, the existing literature is limited to taking regions and sectors as samples and does not provide micro-data experience. Additional new evidence can also help draw more reliable conclusions about the size of the rebound effect.

This paper devotes itself to more detailed analysis and provides more comprehensive information about the behavior response of micro-subjects to fill the research gap. To be more specific, our research measures the energy rebound effect of not only the manufacturing sector but also subsectors following national standards. A dataset of 29 manufacturing subsectors from 2001 to 2008 allows us to present a more detailed and comprehensive estimate. We apply a two-stage method; the energy efficiency is initially calculated and the rebound effect is then estimated with a regression model. The first-step estimate employs a nonparametric estimation method to improve the estimation accuracy. In addition, technological progress is considered when estimating energy efficiency, which alleviates estimation bias and increases reliability. As supplementary, the dynamic effects and regional estimates across subsectors are depicted. Last but not least, we show a wealthy analysis of heterogeneity.

The firm-level dataset enables us to subdivide the manufacturing industry into subsectors to estimate the energy rebound effect by subsector. Theoretically, production technologies vary greatly across different manufacturing subsectors, such that the response of energy consumption to energy efficiency advancement is heterogeneous. Estimating the energy rebound effect by subsectors not only leads to more accurate results but also yields important policy implications. To the best of our knowledge, this paper is among the finest industrial level

studies to show the most comprehensive energy rebound effect in developing countries. The refined measurement reveals hidden details. Surprisingly, when examining the time trends of subsectors, we find that although the macro-level rebound effect is reduced in the long term, this phenomenon does not apply to most subsectors in our sample. Only some high-energy-consuming subsectors show a downward trend similar to the manufacturing sector as a whole. A possible explanation can be that the government monitors and regulates these high-energy-consuming subsectors stringently. Therefore, they must comply with regulations and attempt to control more energy use. Furthermore, the finer-level industrial dynamic effect results imply that this disparity may gradually become more significant. Thus, the achievement of energy saving will worsen for most subsectors as time passes. Roughly implementing a consistent energy efficiency promotion policy for the manufacturing industry is inappropriate. The heterogeneity of subsectors should be considered when formulating policies.

The rest of this article proceeds as follows. We discuss our methodology in Section 2. Variables and data are introduced in Section 3. Our results about average and sectoral static energy rebound effects, dynamic trends, regional comparison, and heterogeneity analyses are shown in Section 4. Section 5 concludes the paper.

2 Methodology

The useful energy service (S) generally requires the energy (E) as input to produce. Sorrell and Dimitropoulos (2008) defined energy efficiency (τ) as the ratio of the energy service to the energy input (i.e., $\tau = S/E$). Service demand remains unchanged ($\Delta S = 0$) when the rebound effect and exogenous shocks do not exist. According to the defined model of energy efficiency, the improvement in energy efficiency leads to an equal decline in energy demand in this specification. Nevertheless, the rebound effect breaks this state. The quantitative relation between energy efficiency and energy demand should be reconsidered. To this end, we employ the efficiency elasticity of energy demand (η_E) to represent changes in energy demand caused by small changes in energy efficiency.

$$\eta_E = \frac{\partial E}{\partial \tau} \frac{\tau}{E}. \tag{1}$$

The following relationship can be derived when we substitute the transformed equation $E = S/\tau$ into Eq. (1):

$$\eta_E = \frac{\partial S}{\partial \tau} \frac{\tau}{S} - 1 = \eta_S - 1, \tag{2}$$

where η_S represents the efficiency elasticity of energy service, which reflects the size of the barrier to energy conservation. Berkhout et al. (2000) took η_S as a direct

measure of the rebound effect (RE).

$$RE = \eta_\text{S} = 1 + \eta_\text{E} = 1 + \frac{\partial \ln E}{\partial \ln \tau}. \qquad (3)$$

A two-stage strategy is adopted to estimate the rebound effect. In the first stage, the energy efficiency (τ) is calculated with the order-α method (see Appendix A for more details). This nonparametric estimation method is ideal for improving estimation accuracy without being affected by outliers and measurement errors. In the second stage, we conduct a regression model to obtain the efficiency elasticity of energy demand (η_E) and thus plus 1 to calculate the rebound effect (RE).

To establish the regression model for efficiency elasticity η_E, we assume a simple production function (i.e., $Q(K, L, \tau E)$). A firm maximizes its profit by setting K, L, and E as follows:

$$\max_{\{K,L,E\}} \pi = pQ(K, L, \tau E) - rK - wL - \delta E, \qquad (4)$$

where K represents capital, L represents labor, p is the product price, r is the capital price or interest rate, w is the labor price or wages, and δ denotes the energy price.

On the basis of Eq. (4) and the principle of profit maximization, we can induce the energy demand function (i.e., $E = D(p, w, r, \delta, \tau)$). Following Li et al. (2019a), a reduced form model is further constituted to investigate the effect of energy efficiency improvement on energy demand, as shown as follows:

$$\ln E_{it} = \eta \ln \tau_{it} + \boldsymbol{\beta}' \boldsymbol{X}_{it} + \alpha_i + \varepsilon_{it}, \qquad (5)$$

where E_{it} and τ_{it} denote the ith firm's energy consumption and energy efficiency, respectively, in year t; $\boldsymbol{X}_{it}$ represents a vector of other logarithmic variables, as shown in the energy demand function, such as the output price ($\ln p_{it}$), labor price ($\ln w_{it}$), capital price ($\ln r_{it}$), and energy price ($\ln \delta_{it}$); η is the coefficient that we are interested in, as the estimate of the efficiency elasticity of energy demand (η_E); coefficient vector $\boldsymbol{\beta}$ denotes the response of energy demand to the prices of output and inputs; α_i represents the ith firm's fixed effect, which captures all unobserved individual factors affecting the energy demand; and ε_{it} is the random error.

3 Variables and data

We obtain the comprehensive firm-level panel data in China, except for Tibet, Hong Kong, Macao, and Taiwan for the period of 2001–2008[1]. These data include industry, region, and time information, which facilitates our estimation of the rebound effect in various subsectors[2]. The measurement and data sources of each variable are as follows.

(1) Energy consumption (E_{it}). Data on a firm's energy consumption is summed by the all-primary energy consumption (i.e., cleaned coal, fuel oil, and clean gas consumption) from China's Environmental Statistics Database. This firm-level database is recently released by the Ministry of Environmental Protection (MEP) and is essential to our study on subsectors.

(2) Energy efficiency (τ_{it}). Energy efficiency is gauged by the approach of order-α, which is introduced in Appendix A; thus, no more discussion is presented here to avoid redundancy. The data about capital stock, the number of employees, and added value come from the Annual Survey of Industrial Firms (ASIF), and the data about energy consumption have been mentioned before. The survey includes all state-owned and non-state-owned firms whose sales are more than 5 million yuan in the manufacturing industry. We can obtain almost all economic indicators of firms, such as gross output, number of employees, wages, fixed assets, debts, and financial fees.

(3) Output price (p_{it}). The output price index by subsector, obtained from the China Premium Database, is used to represent the output price.

(4) Labor price (w_{it}). We use the total wage ratio to the number of employees to denote the firm's labor price. The data about wages and employees are extracted from the ASIF.

(5) Capital price (r_{it}). The capital price is proxied by the interest rate. We use the ratio of financial fees to liability to proxy the firm's interest rate.

(6) Energy price (δ_{it}). We calculate each firm's energy price using the firm's energy consumption and fuel prices. The raw data on fuel prices are collected from the China Premium Database.

Descriptive statistics for the sample are shown in Table 2 after a Winsorized treatment on a 1% quantile. All nominal variables are deflated into the constant prices.

4 Results

4.1 Average energy rebound effect

First, we estimate the average energy rebound effect of China's manufacturing industry as a whole based on Eq. (5). As shown in Table 3, the estimated energy efficiency is −0.377 in Column (1), which yields the energy rebound effect as 62.3%. In other words, more than 60% of the potential energy saving was counterbalanced

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[1] Due to the capital stock and added value (as the measurement of output) missing during 2009–2010 as well as the energy consumption missing after 2011, it is unfeasible to calculate the energy efficiency with the approach of order-α. Thus, the sample is terminated in 2008.

[2] We unify the 2-digit National Standard Industrial Classification (NSIC) codes based on GB/T4754–2002. All subsectors in the manufacturing sector are listed in Appendix B in detail.

Table 2 Summary statistics

Variable	Observation	Mean	Standard deviation	Min	Max
Energy efficiency	218731	0.210	0.340	0.000	2.615
Energy consumption	218731	19507.000	150618.400	2.914	5067999.000
Output price	218731	114.900	24.873	93.125	285.753
Labor price	218731	13757.090	10131.210	1104.252	128119.700
Capital price	218731	0.036	0.052	0.000	0.935
Energy price	218731	525.132	434.167	139.192	2634.507

Table 3 Estimated results for baseline models

Variables	(1)	(2)	(3)
	Energy consumption	Energy consumption	Energy consumption
$\ln \tau^{95}$	−0.377*** (0.017)		
$\ln \tau^{92}$		−0.418*** (0.018)	
$\ln \tau^{98}$			−0.335*** (0.016)
Constant	3.905*** (0.318)	3.990*** (0.309)	3.783*** (0.320)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Observations	199127	199127	199127
R-squared	0.947	0.949	0.944
RE	62.3%	58.2%	66.5%

Notes: 1) Standard errors are clustered at the province level in parentheses; 2) *** represents significance level at 1%; 3) The value of α is 95%, 92%, and 98% for calculating energy efficiency in Columns (1), (2), and (3), respectively.

throughout 2001–2008 because of the rebound effect, and only about 30% of energy input was thus saved.

For the robustness check, we replace the tuning parameter (α value) with 92% and 98% to calculate the energy efficiency and re-estimate the baseline model, respectively. The regression results are reported in Columns (2) and (3). Calculated by the energy efficiency coefficients, the rebound effect reaches 58.2% and 66.5%, respectively. The scale and significance of the rebound effect will stay steady with the change in the value of α, as shown in Table 3.

To explore the evolution of the rebound effect over time, we estimate the dynamic elasticity by replacing the critical variable with the interaction of energy efficiency and an indicator function of time. The regression model is as follows:

$$\ln E_{it} = \gamma \sum_{c=2001}^{2008} \ln \tau_{it} \times I_c(Year) + \boldsymbol{\theta}' \boldsymbol{X}_{it} + \mu_i + \varepsilon_{it}, \quad (6)$$

where γ represents the efficiency elasticity of energy demand for each year, $\boldsymbol{\theta}$ represents the coefficient of the set of control variables, μ_i represents the firm fixed effect, and $I_c(Year)$ is an indicator function described as:

$$I_c(Year) = \begin{cases} 1, & \text{if } Year = c \\ 0, & \text{otherwise} \end{cases}. \quad (7)$$

Figure 2 depicts the dynamic trend of the rebound effect during 2001–2008. The energy rebound effect in the manufacturing industry shows a relatively tiny fluctuation, between 62.7% and 61.9%. In the first few years of the estimate, the rebound effect remained stable. After a peak in 2004 (about 63%), an abrupt downward trend appeared and was maintained. Even in the last year of our data coverage, the effect was still smaller than that in 2001. The possible explanation for the descent after 2004 could be that the Chinese government made effort to implement energy-saving policies with a specific and quantified administrative goal during the 11th Five-year Plan. In addition, compared with the results of Li et al. (2016) and Zhang et al. (2017), the magnitude of the rebound effect in this study is located somewhere in between, and the decreasing trend is similar to their studies.

4.2 Sectoral energy rebound effect

To uncover the rebound effect on a more refined level, we estimate Eq. (5) for each manufacturing subsector. We plot the point estimates alongside the 95% confidence intervals over 2001–2008 in Fig. 3. We also draw a vertical line to indicate the average energy rebound effect for comparison. The rebound effects of all subsectors are partial. No "backfire" effect exists, even when considering
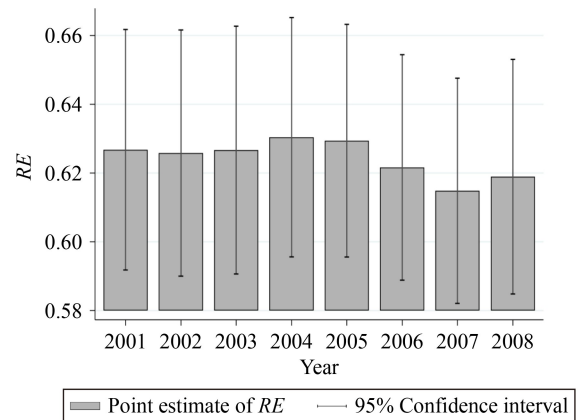
Fig. 2 Dynamic trend of the rebound effect during 2001–2008.
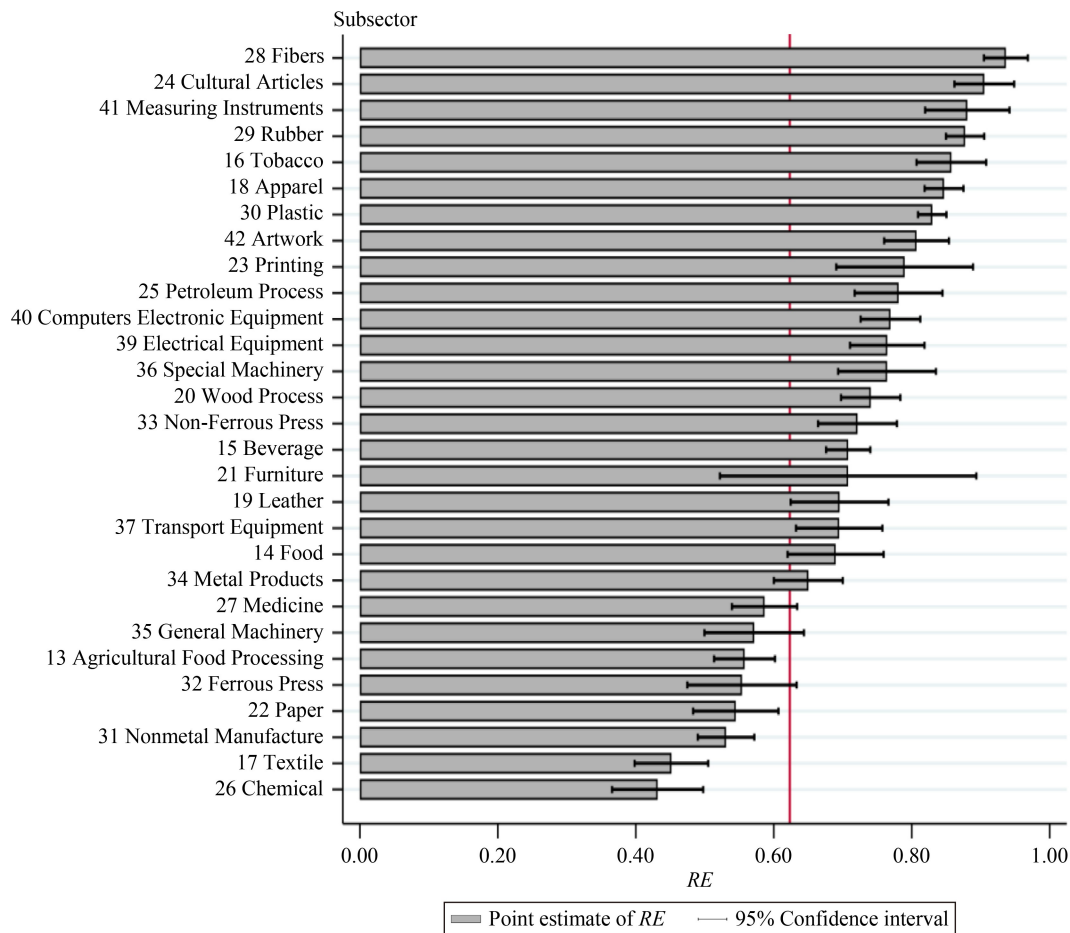
Fig. 3 Energy rebound effect for each subsector in the manufacturing sector (Notes: The energy rebound effect for each subsector is an average over the period of 2001–2008; the red vertical line indicates the average energy rebound effect).

the upper bound of confidence intervals. The point estimates of the rebound effect show a wide disparity from an average of 43.2% for Chemical (No. 26 in Appendix B) to 96.8% for Fibers (No. 28 in Appendix B) over the whole sample period.

In terms of magnitudes, most subsectors have a more significant energy rebound effect than the average rebound effect, except for Medicine (No. 27), General Machinery (No. 35), Agricultural Food Processing (No. 13), Ferrous Press (No. 32), Paper (No. 22), Nonmetal Manufacture (No. 31), Textile (No. 17), and Chemical (No. 26). Coincidently, the latter six subsectors with a lower level than the average rebound effect (62.3%) are the energy- and pollution-intensive subsectors monitored stringently by the government.

### 4.3 Dynamic trend of sectoral energy rebound effect

Can we simply generalize the declining rebound effect trend of manufacturing to all subsectors, similar to what previous macro-level literature does? The fineness of our study allows us to answer this critical question. Similar to Eq. (5), we conduct the regression. Figure 4 depicts the

point estimates of rebound effects alongside the 95% confidence intervals for each subsector from 2001 to 2008. According to the direction of the trend, two groups can be categorized in Panels A and B.

First, most subsectors (21 of 29) have an overall increasing trend of rebound effects during 2001–2008. Specifically, the top three subsectors with incredible growth rates are Medicine (No. 27), Beverage (No. 15), and General Machinery (No. 35), with effect magnitudes of 34.8%, 31.6%, and 23.9%, respectively. We also find that some energy-intensive subsectors have a relatively small growth of about 4%, such as Agricultural Food Processing (No. 13), Textile (No. 17), and Chemical (No. 26). Small increases suggest that the government's critical monitoring of energy-intensive industries restrains the energy rebound effect to some extent.

Moreover, the rebound effects of Cultural Articles (No. 24), Fibers (No. 28), and Rubber (No. 29) reached 90% in 2008. The upper bound of the confidence interval of Cultural Articles (No. 24) even exceeded 100%. This result suggests that energy efficiency improvement has less meaning for these subsectors' energy-saving work.

Second, a decreasing trend is shown for 8 out of 29

Panel A Increasing trend

Panel B Decreasing trend
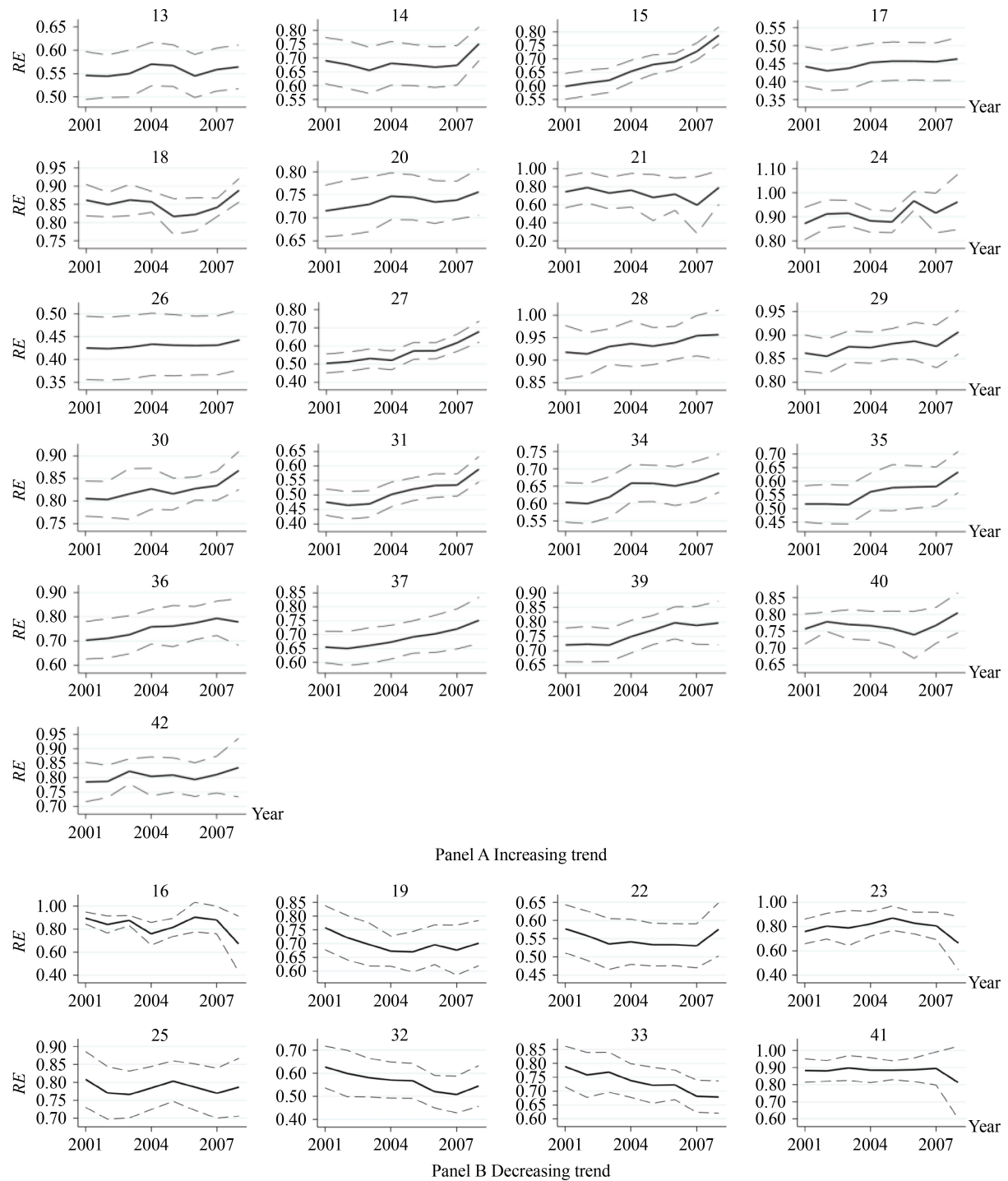
Fig. 4   Energy rebound effects for China's 29 manufacturing subsectors during 2001–2008 (Notes: The solid line connects the point estimates for the rebound effect; the two dashed lines indicate the upper and lower bound of the 95% confidence interval).

subsectors. The three subsectors with the most significant declines are Tobacco (No. 16), Non-Ferrous Press (No. 33), and Ferrous Press (No. 32). In comparison with the giants in Panel A, the descenders' drop size is small (the most significant drop was only 24.9%). However, as we find in Section 4.1, the trend of the macro-level rebound effect complies with these descenders. Through a thor-

ough investigation, high-energy-consuming subsectors are located in the declined group, like Paper (No. 22), Petroleum Process (No. 25), Ferrous Press (No. 32), and Non-Ferrous Press (No. 33). The rebound effects of these subsectors keep weakening, which implies the realization of sufficient energy savings. Given the enormous cardinal number of energy consumption, a slight drop in the

rebound effect in the high-energy-consuming subsector may lead to a considerable energy saving. The decreasing manufacturing dynamic effect implies that this energy-saving effect is significant, even compared with all subsectors as a whole.

4.4   Sectoral energy rebound effect in three regions

After estimating by subsector and time, we further investigate the regional variations of the rebound effect. Following Meng et al. (2011), China is divided into three regions, namely, eastern, central, and western regions[1]. The estimated results are plotted in Fig. 5. Again, energy rebound effects in all subsectors are partial (between 20% and 100%) among the three regions.

The results show that regional heterogeneity exists. Regional estimates of rebound effects are closely distributed around the national average level. Among the three regions, the magnitude in the eastern region is the most similar to that in the whole country. Most subsectors in the less developed western region have a minor effect than the national average. Furthermore, we compare the average effect by region and find that the eastern (64.3%), central (61.6%), and western (57.2%) regions rank in descending order. Specifically, the eastern and central regions are pioneers in 12 and 11 subsectors, respectively. The western region has the slightest concern about rebound effects in most subsectors. Nevertheless, six subsectors in the western region have the most remarkable rebound effect (i.e., Tobacco (No. 16), Leather (No. 19),

Petroleum Process (No. 25), Nonmetal Manufacture (No. 31), Computers Electronic Equipment (No. 40), and Measuring Instruments (No. 41)). For the identification of extreme values in the three regions, the most considerable rebound effect appears in Fibers (No. 28), Cultural Articles (No. 24), and Measuring Instruments (No. 41); on the contrary, the lowest effect appears in Textile (No. 17), Chemical (No. 26), and Furniture (No. 21).

As shown in Fig. 5, we can notably find that the disparity across regions is considerably smaller than that across subsectors. Precisely, the discrepancy of rebound effects across subsectors reaches 65.5%, whereas the discrepancy across regions is only 42.4%. Most subsectors realize similar magnitudes among the three regions, such as Tobacco (No. 16), Petroleum Process (No. 25), Medicine (No. 27), Fibers (No. 28), Rubber (No. 29), and Nonmetal Manufacture (No. 31). Values in other subsectors differ between regions, but the gap is insignificant, except for Furniture (No. 21).

4.5   Heterogeneity of energy rebound effect

The sensitive group identification of the rebound effect is widely concerned. This section aims to analyze the heterogeneity of rebound effects among subsectors or regions. The results are concretely reported in Table 4. In all specifications, the coefficients of the subsample are significantly different, examined by Fisher's permutation test, referring to Cleary (1999) and Lian et al. (2010).

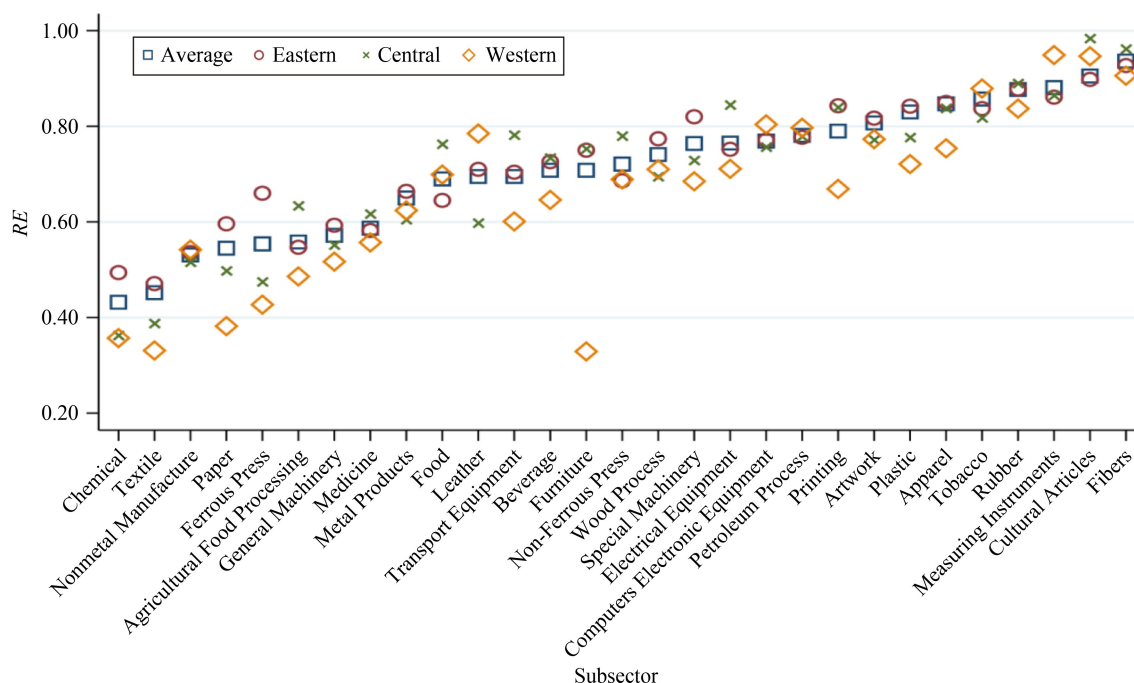Generally, energy-intensive industries are under the

Fig. 5   Energy rebound effect in three regions for 29 manufacturing subsectors.

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[1] Appendix C presents the classification of regions, where Tibet, Hong Kong, Macao, and Taiwan are not included.

Table 4 Results of heterogeneity analysis

Variables	(1) Energy-intensive	(2) Non-energy-intensive	(3) Pollution-intensive	(4) Non-pollution-intensive	(5) High industry concentration	(6) Low industry concentration	(7) Heavy industry	(8) Light industry	(9) High-degree of marketization	(10) Low-degree of marketization
$\ln \tau^{95}$	−0.436*** (0.0182)	−0.330*** (0.0186)	−0.417*** (0.0163)	−0.271*** (0.0185)	−0.283*** (0.0175)	−0.496*** (0.0205)	−0.382*** (0.0181)	−0.366*** (0.0195)	−0.350*** (0.0266)	−0.400*** (0.0208)
Constant	5.395*** (0.219)	2.820*** (0.508)	4.841*** (0.224)	1.521** (0.690)	4.122*** (0.344)	4.492*** (0.236)	4.160*** (0.326)	3.107*** (0.570)	3.767*** (0.475)	3.990*** (0.477)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97568	100914	161837	37290	89410	100596	124734	74393	97270	99747
R-squared	0.948	0.923	0.949	0.912	0.944	0.957	0.951	0.931	0.944	0.948
RE	56.4%	67.0%	58.3%	72.9%	71.7%	50.4%	61.8%	63.4%	65.0%	60.0%
Empirical p-value	0.000***		0.000***		0.000***		0.018**		0.000***	

Notes: 1) Standard errors are clustered at the province level in parentheses; 2) *** and ** represent significance levels at 1% and 5%, respectively; 3) The empirical p-value is the result of Fisher's permutation test. The null hypothesis of Fisher's permutation test is that the coefficients between two groups are equal. The empirical p-value is the percentage of simulations, where the difference in the empirical sample's coefficients exceeds the difference in the actual sample's coefficients in a bootstrapping procedure. The number of repetitions is 1000. More technical details can be found in Cleary (1999).

uppermost supervision and monitoring by governments, thereby having a lower rebound effect. We use the ratio of the subsector's energy consumption over the number of employees to measure the energy intensity. As shown in Columns (1) and (2) of Table 4, the energy efficiencies in the energy-intensive and non-energy-intensive sub-sectors are −0.436 and −0.330, respectively. The result implies that energy-intensive subsectors have more small-scale rebound effects, consistent with the conclusion in Fig. 3 in Section 4.2.

It is reasonable to suspect that the rebound effects of energy efficiency vary by pollution intensity. Pollution-intensive subsectors face more stringent regulations because of massive energy consumption and pollution emissions, such as the energy-intensive subsectors. According to the document released by MEP, a sector is considered pollution-intensive if it belongs to the environmental inspection sectors. The estimated results are reported in Columns (3) and (4). The rebound effects are calculated as 58.3% and 72.9% in the pollution-intensive and non-pollution-intensive subsectors, respectively, indicating that pollution-intensive subsectors' rebound effects are minor in scale.

The higher the industry concentration is, the lower the degree of market competition will be. The monopoly power may make the output effect mechanism more effective and thus lead to a high-level rebound effect. Furthermore, we speculate that energy-saving policies restrict monopolies with higher industry concentration less due to their close relationship with the government. We use the sales ratio of the top four largest firms over the entire industry to measure the degree of industry concentration. As shown in Columns (5) and (6) in Table 4, the rebound effect of subsectors with high concentrations is 20% higher than that with low concentrations.

Chakravarty et al. (2013) contended that the light industry is more likely to change energy consumption and has a more significant rebound effect than the heavy industry. According to China's National Bureau of Statistics, the sample is classified as heavy industry and light industry. From Columns (7) and (8), an interesting finding consistent with Liu et al. (2019) is noticed that the light industry has a greater rebound effect. One reasonable explanation is the light industry is driven by the substitution effect strongly and replaces other inputs with more energy. Conversely, the heavy industry with large energy consumption cannot expend too much energy, facing stringent regulations.

Li et al. (2019a) asserted that marketization will affect firms' operation flexibility and eventually influence the rebound effect. Therefore, we divide the regions into two groups according to the marketization index. Referring to Fan et al. (2011), the index reflects regional economies' marketization degree. The results by the group are shown in Columns (9) and (10). In comparison with the high-degree region, the energy consumption in low-degree marketization regions declines more. As expected, this finding reveals that the magnitude of the rebound effect is more prominent in the regions with high degrees of marketization, verifying the conclusion of Li et al. (2019a). In the regions with high-degree marketization, firms have more flexibility in production decisions and thus have larger rebound effects.

5 Conclusions and policy implications

This study estimates the energy rebound effect for all 29 subsectors in China's manufacturing sector from 2001 to 2008. We apply a two-stage method; the order-α method is initially used to calculate the firm's energy efficiency by year and subsector and a regression model is then utilized to estimate each subsector's static and dynamic rebound effects. We also explore the disparity of the

rebound effects at the sectoral and regional levels.

According to our results, China's energy rebound effect of manufacturing is 62.3%, indicating that 37.7% of initially expected energy savings are achieved under the energy efficiency improvement. The results remain robust when replacing the value of α for energy efficiency estimation. Moreover, a slightly decreasing trend of the rebound effect emerged during 2001–2008, especially after 2004.

Second, from the subsectors' perspective, the magnitudes of rebound effects are described as partial effects for all subsectors, indicating that the energy efficiency improvement does not offset the energy conservation thoroughly. Moreover, the results show a wide disparity ranging from 43.2% for Chemical (No. 26) to 96.8% for Fibers (No. 28) over the entire sample period. We also find that most subsectors (21 of 29) keep increasing, with a scale ranging from 34.8% to 3.4%. On the contrary, some high-energy-consuming subsectors present a lower increasing trend or even a decreasing trend of the energy rebound effect.

Third, from the perspective of the regions, the energy rebound effects for the developed eastern region are close to the average rebound effects among most subsectors. By contrast, the less developed western region's rebound effect presents a lower level than the average rebound effect. Furthermore, we find that the disparity of the rebound effect across subsectors is more significant than that across regions.

Fourth, the rebound effects vary among industries and markets. The larger magnitudes of rebound effects exist for the non-energy-intensive industry, non-pollution-intensive industry, the high-concentration industry, the light industry, and the high degree of marketization region.

In addition, our results provide important implications for academics and policymakers. From a theoretical point of view, this paper remedies the research gap in energy rebound effects at a finer industrial level, as mentioned in Zhang et al. (2017), and thus enhances the understanding of more detailed rebound effects for each subsector in China's manufacturing sector.

We can also distill vital implications from a policy perspective. First, our empirical studies reveal the confusing mystery that Chinese government devotes excessive effort to energy efficiency improvement and energy conservation, but with little success. Precisely, the energy rebound effect hinders achieving energy-saving goals. Given that the energy consumption by the manufacturing industry accounts for the most significant proportion of the total energy consumption in the aggregate industry, policymakers should pay more extra attention to the manufacturing industry's rebound effect.

As for various subsectors, different strategies for energy conservation should be designed and implemented. Exploring sectoral rebound effects in China's manufacturing industry helps policymakers to identify subsectors where energy-saving is more likely achieved by energy efficiency improvement. For example, given that energy efficiency improvement is quite effective for those subsectors whose rebound effects are below the average magnitude (e.g., Chemical, Textile, Nonmetal Manufacturing, Paper, Ferrous Press, Agricultural Food Processing, General Machinery, and Medicine), more stringent energy efficiency goals are applicable. Conversely, for subsectors with substantial rebound effects, some complementary measures should be adopted (e.g., available tax and subsidy policies) to alleviate unexpected outcomes from efficiency improvement.

Finally, unfortunately, our research sample ended in 2008 due to data unavailability. As for further research, except for extending the research sample, investigating the relationship between the carbon rebound effect and carbon efficiency in the manufacturing industry would be worth exploring, in addition to the energy rebound effects.

Appendix A. Measuring energy efficiency

In the existing literature, several approaches are used for measuring efficiency. Aigner et al. (1977) and Meeusen and van den Broeck (1977) proposed the stochastic frontier analysis (SFA). The parametric method is based on the specific production function and certain assumptions about the distribution of random errors and the functional form. The SFA not only captures the random noise by the traditional two-sided error term but also allows to measure inefficiency by a composed one-sided error term. However, Adetutu et al. (2016) also stated that using SFA to estimate energy efficiency is underscored by criticisms. One of the most prevalent criticisms is relying on strict assumptions about the specific functional forms and the distribution of random errors. In addition, Tauchmann (2012) pointed out that the SFA only accommodates single-output technologies if a production frontier is estimated.

Another brand of literature is about the nonparametric method. The most famous and widely used methods are the data envelopment analysis (DEA) proposed by Charnes et al. (1978) and the free disposal hull (FDH) approach proposed by Deprins et al. (2006). The two methods nonparametrically envelop a provided sample with a segmented linear hull and are characterized by deterministic approaches (Tauchmann, 2012). The DEA assumes a convex technology and envelops the data by linear programming (Wu et al., 2021). The FDH gives up the assumption of a convex technology and envelops the data by a nonconvex staircase-hull based on the principle of weak dominance. However, the two approaches are commonly criticized for lacking a definite data generating

processing and easily influenced by outliers and measurement errors.

Recently, the latter drawback of the nonparametric methods has been improved by partial frontier approaches, specifically order-m and order-α. In conclusion, this paper complies with this stream of methods to measure energy efficiency. Order-m and order-α are generalizations of the FDH, but order-α can be computed faster than order-m because resampling procedures are unnecessary. Thus, we finally adopt the order-α method to compute energy efficiency. Before we use the order-α to estimate energy efficiency, we initially define the energy distance function and energy efficiency (τ).

We assume that there exist $i = 1, ..., N$ decision-making units (i.e., firms). Each firm can use capital, labor, and energy, denoted by K, L, and E, respectively, to produce the desired output, marked by Y. Suppose that there exist $v = 1, ..., V$ subsectors in the manufacturing sector. We conduct global production technology for each subsector, such that each subsector has a global benchmark. The change in efficiency reflects the distance to the frontier, which is driven by changes in energy technology and energy utilization efficiency. The v subsector-specific global production technology can be described as:

$$P^v = \left\{ \begin{array}{l} (K, L, E, Y) \in \mathbb{R}_+^{p+q} | Y \leqslant Y_{it}, K \geqslant K_{it}, L \geqslant L_{it}, E \geqslant E_{it} \\ i = 1, ..., N; t = 1, ..., T \end{array} \right\}.$$
(A.1)

As shown in Eq. (A.1), the actual inputs are equal to or larger than the frontier of inputs, and the actual output is equal to or smaller than the frontier of output in the global production technology. On the basis of the formulation of the global production technology, following Zhou et al. (2012), we define the Shephard energy distance function as follows:

$$D_E^v(K, L, E, Y) = \sup\{\tau | (E/\tau, K, L, Y) \in P^v\},$$
$$v = 1, ..., V. \quad (A.2)$$

Different from the conventional Shephard distance function, the Shephard energy distance function does not need to change all inputs used simultaneously. Subsectors only adjust energy use to close to the frontier while keeping the other inputs and output constant under the production technology. Obviously, $E/D_E^v(K, L, E, Y)$ reflects the theoretical energy use if a firm uses the subsector's technology most efficiently. Energy efficiency (EE) is defined as the ratio of theoretical energy use to actual energy use, which equals the reciprocal of the distance function:

$$EE = 1/D_E^v(K, L, E, Y). \quad (A.3)$$

On the basis of this theoretical measure, we attempt to put it in a practical perspective. Given that order-α is the generalization of the FDH, we initially discuss the FDH. On the basis of Deprins et al. (2006), here, peer firms are constructed by each firm i and all other firms j that produce at least as much output as firm i. The FDH method takes the best performing unit with minimum energy consumption as a reference to i. The efficiency value $\hat{\tau}_i^{\mathrm{FDH}}$ is computed as the relative energy use, as shown as follows:

$$\hat{\tau}_i^{\mathrm{FDH}} = \min_{j \in B_i}\left\{\frac{E_j}{E_i}\right\}, \quad (A.4)$$

where B_i represents the set of firms that produce at least as much output as firm i. Given the problem of sensitivity to outliers and measurement errors within the FDH, the order-α method uses the $(100 - \alpha)$th percentile energy consumption among the available peers as a benchmark, which is more robust to noises and is described as follows:

$$\hat{\tau}_i^{\mathrm{OA}} = P_{\substack{(100-\alpha) \\ j \in B_i}}\left\{\frac{E_j}{E_i}\right\}. \quad (A.5)$$

Particularly, α can be considered a tuning parameter that determines how many firms are enveloped by the estimated production frontier. When α equals 100, the order-α agrees with the FDH. However, when the α is smaller than 100, some firms may be identified as super-efficient units.

In practice, we use Stata's orderalpha command to yield our estimation of energy efficiency. More information about the command can be found in the paper of Tauchmann (2012).

Appendix B. List of manufacturing subsectors and abbreviations

Table B1 List of manufacturing subsectors and abbreviations

Complementary Identification Code	Subsector	Abbreviation
13	Processing of food from agricultural products	Agricultural Food Processing
14	Manufacture of foods	Food
15	Manufacture of beverages	Beverage
16	Manufacture of tobacco	Tobacco

Complementary Identification Code	Subsector	Abbreviation
17	Manufacture of textile	Textile
18	Manufacture of textile wearing apparel, footwear and caps	Apparel
19	Manufacture of leather, fur, feather and related products	Leather
20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products	Wood Process
21	Manufacture of furniture	Furniture
22	Manufacture of paper and paper products	Paper
23	Printing, reproduction of recording media	Printing
24	Manufacture of articles for culture, education and sport activities	Cultural Articles
25	Processing of petroleum, coking, processing of nuclear fuel	Petroleum Process
26	Manufacture of raw chemical materials and chemical products	Chemical
27	Manufacture of medicines	Medicine
28	Manufacture of chemical fibers	Fibers
29	Manufacture of rubber products	Rubber
30	Manufacture of plastics products	Plastic
31	Manufacture of nonmetallic mineral products	Nonmetal Manufacture
32	Smelting and pressing of ferrous metals	Ferrous Press
33	Smelting and pressing of non-ferrous metals	Non-Ferrous Press
34	Manufacture of metal products	Metal Products
35	Manufacture of general purpose machinery	General Machinery
36	Manufacture of special purpose machinery	Special Machinery
37	Manufacture of transport equipment	Transport Equipment
39	Manufacture of electrical machinery and equipment	Electrical Equipment
40	Manufacture of communication equipment, computers and other electronic equipment	Computers Electronic Equipment
41	Manufacture of measuring instruments and machinery for cultural activity and office work	Measuring Instruments
42	Artwork and other manufacturing	Artwork

Appendix C. Classification of the three regions in China

Table C1   Classification of the three regions in China

Region	Provinces or Municipalities
Eastern region	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Hebei, Shandong, Liaoning, Guangxi
Central region	Heilongjiang, Jilin, Anhui, Henan, Hubei, Hunan, Jiangxi, Inner Mongolia, Shanxi
Western region	Chongqing, Gansu, Guizhou, Ningxia, Qinghai, Sichuan, Xinjiang, Shaanxi, Yunnan

Note: Tibet, Hong Kong, Macao, and Taiwan are not included in the research samples.

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