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The changes in coal intensity of electricity generation in Chinese coal-fired power plants☆

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ABSTRACT

In recent years, the coal intensity of electricity generation and its change rate over time has varied significantly across coal-fired power plants in China. This paper decomposes the coal intensity change into four components: technological catch-up, technological progress, change in capital-coal ratio, and change in labor-coal ratio. We find that technological catch-up is the most important factor in decreasing mean coal intensity in the plants between 2009 and 2012. It is also the main driver of heterogeneity in coal intensity changes across different groups of the plants.

1. Introduction

China's energy supply depends heavily on coal. In 2016, the country consumed four billion tons of coal (NBS, 2017), which accounted for nearly half of the global coal consumption. The burning of coal emits a large amount of greenhouse gases and pollutants such as sulfur dioxide and particulate matter. It is thought to be one of the most important factors leading to a large number of annual smoggy days across China in recent years, especially in the northern provinces where coal resources and heavy industries are concentrated. To reduce and control air pollution, the central government is attempting to limit coal consumption. It is also critical to the goals of reducing the carbon dioxide intensity of the national economy in 2020[1] and peaking carbon dioxide emission in 2030.[2] Limiting coal consumption in thermal power plants is an important part of the endeavors, as coal-fired power sector is the largest consumer of coal in China. Therefore, the government pays a lot of attention to this sector when it makes energy and climate change relevant policies. For instance, China launched the world's largest carbon-trading program in December 2017; at its initial stage, this national program covered about 1700 of the country's thermal power firms.

Coal intensity is a key technical and economic indicator for evaluating the performance of a coal-fired power plant. It measures the amount of coal consumed per kilowatt-hour (kWh) of net electricity generation. The literature mainly focuses on power plants' total factor productivity, carbon emissions, and shadow price of carbon and pollutants. For example, recent studies on China's power plants found that electricity reforms in the early 2000s[3] improved productivity of power plants (Du et al., 2013). In addition, the contributions from technology mandates and market restructuring on efficiency improvement were also significant (Ma and Zhao, 2015). Moreover, using data on Chinese thermal power enterprises, Wei et al. (2013) estimated the shadow price of carbon dioxide. They found large inefficiencies in electricity production and carbon dioxide emissions. Finally, Zhang et al. (2014) suggested

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[1] In November 2009, China announced targets to reduce the intensity of carbon dioxide emissions per unit of GDP in 2020 by 40 to 45% compared with the level of 2005.

[2] In November 2014, China announced targets to peak carbon dioxide emissions around 2030 and try to peak early, and to increase the non-fossil fuel share of all energy to about 20% by 2030.

[3] In 2002, China's central government initiated a new round of electricity reform. A key measure was dismantling the former State Power Corporation and founded eleven smaller companies which include two electric power grid operators, five electric power generation companies and four relevant business companies.

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that larger fossil fuel power plants in China had better unified energy and carbon efficiency. However, we have not located any studies examining coal intensity of electricity generation and its changes over time. The paper is also motivated by the observed heterogeneity among power plants in terms of coal intensity.

The goal of this paper is to understand the dynamics of coal intensity of electricity generation in Chinese power plants[4] and its determinants. This paper contributes to the literature in two ways. First, we construct a unique plant-level dataset for 2009 and 2012 for the analysis on coal intensity change. It includes detailed information on inputs and net electricity generation (output) for major coal-fired power plants in China.

Second, we check whether the impacts of the driving factors for coal intensity change differ across firms of different ownerships, sizes, and regions. However, it should be noted that the decomposition analysis can be viewed as an accounting exercise which generates new results regarding the source of changes in coal intensity of electricity generation in coal-fired power plants; it does not provide fundamental reasons for the changes (Wang, 2013).

The paper is closely related to the literature on energy decomposition (Ang and Zhang, 2000). We use output distance functions and data envelopment analysis to model coal as an input factor in the process of producing electricity along with other input factors such as capital and labor. Using the constructed dataset, we decompose the coal intensity change in a plant between two years into four components: technological catch-up, technological progress, change in capital-coal ratio, and change in labor-coal ratio. The results provide evidence at firm level to help us understand the potential in improving efficiency of using coal in the coal-fired power plants. We also use a nonparametric analysis (Li, 1996, 1999) to statistically test the relative contributions of the preceding four components and their roles in the distribution dynamics of coal intensity. We use physical measures for coal and electricity in the empirical analysis of coal intensity. This avoids the impacts of market power on prices which might severely bias our estimates of productivity if we use monetary values for inputs and outputs. Previous studies in the related literature also used physical measures for coal and electricity to investigate energy and CO_2 emission performance in electricity generation (Zhou et al., 2012) and the effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants (Zhang et al., 2014). From the perspective of the output functions, we use gross output measured in physical units, but not value added as in Wang (2011, 2013) and some others on energy intensity. This is reasonable in this specific line of energy decomposition literature because it focuses on finding the determinants of changes in energy intensity.

Major findings of the paper can be summarized as follows: 1) the decrease in mean coal intensity of the coal-fired power firms was mainly driven by technological catch-up from 2009 to 2012; 2) the catch-up was also the main factor driving different patterns of coal intensity change among various firm groups; 3) as their capital stock increased, small firms[5] performed relatively better in improving their coal intensity. Our analysis allows us to identify coal-fired power plants that produce electricity technically inefficiently. The results imply that policy interventions should focus more on improving technical efficiency of firms in terms of using input factors like coal. Our work suggests that the small firms that located in the western regions of the country are the best candidates for policy interventions. These firms are relatively technically inefficient (and far from the best practices of using coal and other input factors) in generating electricity.

The remainder of the paper is organized as follows. Section 2 describes data. Section 3 briefly develops a framework for decomposing coal intensity change into four components. Section 4 reports decomposition results, discusses heterogeneity, and checks the robustness of the results. Section 5 presents more analyses on the distribution dynamics of firms' coal intensity. The final section concludes the paper.

Table 1
Summary statistics.

	N	Min	Max	Mean	Std
Year = 2009	488				
Capital		32.87	25,483.08	4092.07	3502.96
Labor		85.93	76,000.99	6896.47	6903.10
Coal		9.53	6791.24	1261.29	1002.80
Electricity		32.11	20,660.29	3757.45	3152.75
Coal intensity (CI)		282.16	604.86	352.16	36.89
Year = 2012	532				
Capital		33.43	203,463.70	5195.83	10,422.95
Labor		55.00	198,179.00	6125.18	10,549.40
Coal		10.20	56,163.90	1542.28	2869.57
Electricity		19.14	184,966.40	4751.46	9326.61
Coal intensity (CI)		281.05	731.09	339.34	43.50
2009–2012	389				
CI change (%)		−27.41	111.62	−2.27	11.58

Note: Capital is the product of electricity generation capacity (million kW) and hours operated and measured in mkWh, labor is wage payment and measured in 10 thousand *yuan* (2012 RMB), coal is the consumed coal by plants and measured in thousand tonnes, electricity is the output of the plants and measured in in million kWh, and coal intensity is measured in grams of coal equivalent per kWh of electricity.

2. Data

Our main data source is the *Compilation of Statistics on Electricity Regulation*. The Compilation was edited by the former State Electricity Regulatory Commission (SERC).[6] Each year, power firms in China reported data on its inputs and outputs to the SERC. After receiving the reports, SERC reviewed and compiled the data. Due to data restrictions, we only have access to the *Compilations* for 2009 (SERC Information Center, 2011) and 2012.[7] Main variables include power plant capacity, mean hours of operation, wage payment, coal consumption, and net electricity generation. We use the product of the capacity and mean hours of operation[8] to represent capital input in the production function. Following previous studies (e.g., Brandt et al., 2012), we use wage payment[9] as labor input because it could capture hours worked and accumulated human capital content. Using consumer price index (NBS, 2013), we measure wage payment in 2012 renminbi (or RMB, Chinese currency).

We limit data sample to those coal-fired power plants which produce only electricity. That is, firms which produce both electricity and any other product such as heat are excluded from the final data sample. For each year, we drop those firms whose coal intensity of net electricity generation is not within (280–800) grams of coal equivalent (hereafter, *gce*) per kWh of net electricity generation. This is a large interval given that the national mean level was around 340 *gce* per kWh in 2009 (NBS, 2013). We also delete those observations which have missing values for wage payment, capacity, hours of operation, or net electricity generation. The constructed dataset contains 488 firms and 532 firms for the years 2009 and 2012, respectively. The information of 389 of the firms is available for both years.

Based on the obtained sample, we calculate changes in coal intensity and other variables between 2009 and 2012. Table 1 reports summary statistics. An average firm produced 4.75 billion kWh of electricity in

4 "Plant" and "firm" are exchangeable in the present paper.
5 Small firms are defined based on capital stock. Section 4 will provide more details on this point.

6 In 2013, the Commission was merged with other government agencies to form the National Energy Administration.
7 For the 2012 data, as there are no published print versions of the Compilations, we use electronic files provided by the SERC.
8 Operation hours of electricity generators are under regulation in China. Similar types of generators are allocated roughly the same number of generation hours (Ding and Yang, 2013).
9 Wage payment here does not include housing benefits, unemployment insurance, retirement benefits, or health insurance.

2012. It suggests that the coal-fired power plants in our sample produced 2528 billion kWh in 2012. This is to say, our sampled firms generated about 71% of total amount of coal electricity produced by thermal power plants in the whole country (NBS, 2013). This shows that our sample is a good representation of the coal-fired power sector in China.

As shown in Table 1, the mean level of coal intensity is 352 *gce* per kWh in 2009, while the weighted (by net electricity generation) mean is 336 *gce* per kWh.[10] For 2012, the numbers are 339 and 325, respectively. The levels are almost the same as the national means. In 2012, coal intensity in China's coal-fired power plants was 325 *gce* per kWh.

Table 1 shows a large variation in coal intensity of the firms for each year. In 2009, the maximum coal intensity was 605 *gce* per kWh, while the minimum was 282. In 2012, the maximum was about 2.6 times as much as the minimum. Additionally, change rate in coal intensity also varied a lot during the time period. Table 1 indicates that mean growth rate between 2009 and 2012 was −2.27%. The highest rate was 111.62%, while the lowest one was −27.41%. To give some more details, Fig. 1 plots the distributions of coal intensity in 389 common firms for the years of 2009 and 2012. It suggests that the mass of the distribution significantly shifted leftward over this 4-year period.[11] A related question is: What are the drivers for the decrease in the mean coal intensity between 2009 and 2012? From the perspective of production theory, it could be caused by an increase in total factor productivity (e.g. technological catch-up and/or technological progress) or substitution between inputs such as labor-coal or capital-coal.[12]

3. A decomposition framework

In this section, we briefly describe a decomposition framework to examine the sources of changes in coal intensity for coal-fired power plants over time. More details can be found in Appendix A. The framework is very similar to the one developed in Wang (2007, 2013) for investigating energy intensity of national economy. It is a modification and extension of the framework on labor productivity proposed by Kumar and Russell (2002) and Henderson and Russell (2005). Here, we consider a typical coal-fired power plant which uses three inputs: capital, labor, and coal, to produce electricity. Using Shephard output distance functions (Shephard, 1970) and the "ideal" index-number formula proposed by Seigel (1945), the coal intensity change is decomposed into several components.

For each year $t = 1, 2, \ldots, T$, production technology for a coal-fired power plant is given by the set

$$S^t = \{(K_t, L_t, C_t, E_t) : (K_t, L_t, C_t) \textit{ can produce } E_t\}, \tag{1}$$

where the variables are capital (K_t), labor (L_t), and coal (C_t), and net electricity generation (E_t).[13] Standard conditions which suffice to define output distance functions are imposed on the production set S^t (Färe, 1988). The output distance function at year t is defined as

$$D_o^t(K_t, L_t, C_t, E_t) = \inf\{\theta : (K_t, L_t, C_t, E_t/\theta) \in S^t\}. \tag{2}$$

The function measures the maximum feasible expansion of the observed actual net electricity generated, E_t, given the input vector, (K_t, L_t, C_t), and the technology, S^t. In other words, it calculates how far the observed net electricity production is from maximum potential production.

The value of the distance function is defined as "technical efficiency" (Färe et al., 1994) of the power plant. It ranges from 0 to 1. It is equal to one if and only if the observation (K_t, L_t, C_t, E_t) is on the boundary or frontier of the technology, S^t. Given production technology and input bundle, higher output indicates a higher value of the function which means that the firm is technically more efficient.

We further assume that the production technology of the firms exhibit constant-returns-to-scale (CRS) technology.[14] For notational convenience, we let $k_t \equiv K_t/C_t$ and $l_t \equiv L_t/C_t$ which denote capital-coal ratio and labor-coal ratio, respectively. Using output distance functions and production technology at year t as a reference, we can decompose the coal intensity change in a plant between years t and τ in the following way:

$$\begin{aligned} \frac{C_\tau/E_\tau}{C_t/E_t} &= \frac{D_o^t(K_t, L_t, C_t, E_t)}{D_o^\tau(K_\tau, L_\tau, C_\tau, E_\tau)} \times \frac{D_o^\tau(K_\tau, L_\tau, C_\tau, E_\tau)}{D_o^t(K_\tau, L_\tau, C_\tau, E_\tau)} \\ &\quad \times \left\{ \frac{D_o^t(k_\tau, L_t, 1, 1)}{D_o^t(k_t, L_t, 1, 1)} \cdot \frac{D_o^t(k_\tau, L_\tau, 1, 1)}{D_o^t(k_t, L_\tau, 1, 1)} \right\}^{\frac{1}{2}} \\ &\quad \times \left\{ \frac{D_o^t(k_t, L_\tau, 1, 1)}{D_o^t(k_t, L_t, 1, 1)} \cdot \frac{D_o^t(k_\tau, L_\tau, 1, 1)}{D_o^t(k_\tau, L_t, 1, 1)} \right\}^{\frac{1}{2}} \\ &\equiv EFF \times TECH(\tau) \times KC^t \times LC^t. \end{aligned} \tag{3}$$

Appendix A provides more details on how the decomposition (3) is obtained. As discussed earlier in this section, $D_o^t(K_\tau, L_\tau, C_\tau, E_\tau)$ measures the maximal change in output required to make $(K_\tau, L_\tau, C_\tau, E_\tau)$ feasible in relation to the production technology S^t. Thus, the second term in the decomposition (3), $\frac{D_o^\tau(K_\tau, L_\tau, C_\tau, E_\tau)}{D_o^t(K_\tau, L_\tau, C_\tau, E_\tau)}$, measures technological progress (i.e. the shift of the production frontier) between the two years evaluated at $(K_\tau, L_\tau, C_\tau, E_\tau)$. If technology at year τ is more advanced than that at year t, then the following condition holds: $D_o^\tau(K_\tau, L_\tau, C_\tau, E_\tau) < D_o^t(K_\tau, L_\tau, C_\tau, E_\tau)$. If we use the production technology in year τ instead of the one in year t as a reference, decomposition (3) takes the following form:

$$\frac{C_\tau/E_\tau}{C_t/E_t} = EFF \times TECH(t) \times KC^\tau \times LC^\tau. \tag{4}$$

We can avoid the ambiguity of choosing one of the decompositions in (3) and (4) by calculating the geometric mean of the two decompositions, then the coal intensity change is given by

$$\begin{aligned} \frac{C_\tau/E_\tau}{C_t/E_t} &= EFF \times [TECH(\tau) \cdot TECH(t)]^{\frac{1}{2}} \times \left[KC^t \cdot KC^\tau\right]^{\frac{1}{2}} \times \left[LC^t \cdot LC^\tau\right]^{\frac{1}{2}} \\ &\equiv EFF \times TECH \times KC \times LC. \end{aligned} \tag{5}$$

This shows that coal intensity change can be decomposed into four components. The first component measures the effect of technological catch-up (or "technical efficiency change" as used by Färe et al. (1994)). If there is technological catch-up in year τ relative to year t (i.e., $EFF < 1$), then this component aids in lowering the coal intensity. The second component measures technological progress. The technological progress in year τ (i.e., $TECH < 1$) contributes to declines of coal

[10] The table indicates that, in 2009, an average firm produces 3.76 billion kWh of electricity using 1.26 trillion grams of coal equivalent (*gce*). It implies that the weighted mean is 336 *gce* per kWh.

[11] This paper uses the Gaussian kernel function to estimate the densities. To determine the "optimal" bandwidth, we use the Sheather and Jones (1991) selector.

[12] Kumar and Russell (2002) showed that capital deepening (i.e., increase in capital-labor ratio) has a positive impact on labor productivity. Wang (2011, 2013) found that the change in capital-energy ratio and the change in labor-energy ratio affect energy intensity changes in China and other countries in the world.

[13] As described in Table 1, inputs are in million kW∗hours (capital), 10,000 yuan (labor), and 1000 tons (coal). As in standard production functions (Färe et al., 1994), the choosing of measurement units of inputs and measurement unit of the output does not affect the estimation results.

[14] It might be the case that a power plant's true technology is not CRS. However, the CRS technology "provides bounds on the underlying true-but unknown-technology", and it captures a "long run" (Färe et al., 1997). Previous studies on total factor productivity (Färe et al., 1994; Färe et al., 1997), labor productivity (Kumar and Russell, 2002; Henderson and Russell, 2005), and energy intensity (Murillo-Zamorano, 2005; Wang, 2007, 2011, 2013) also assume CRS technology.

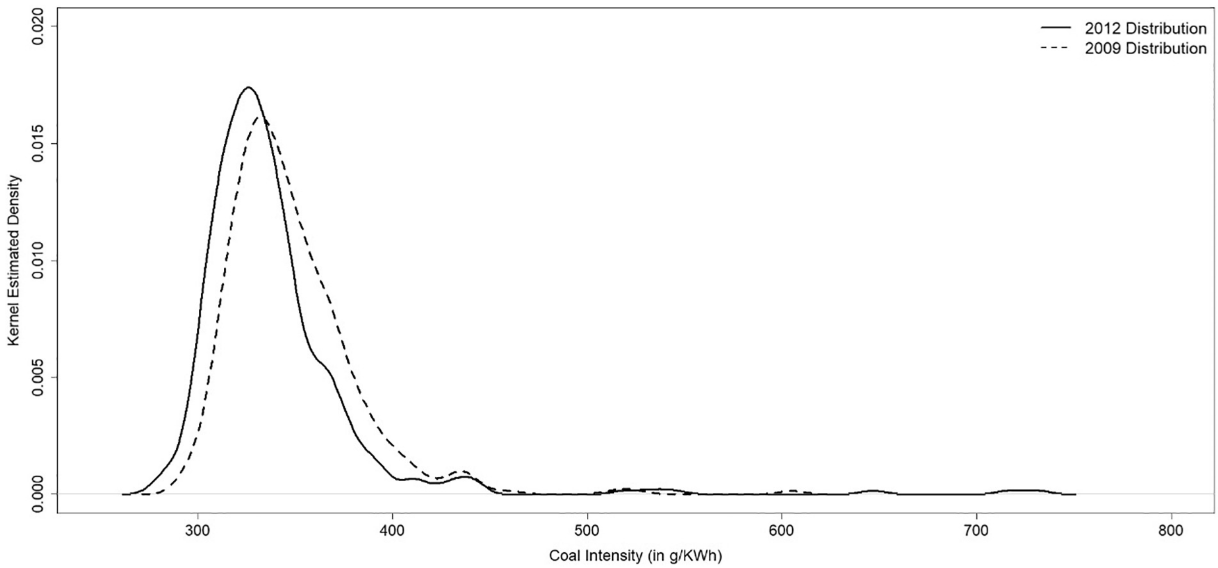

Fig. 1. Distribution of coal intensity in 2009 and 2012.

intensity. The combination of the first two components in Eq. (5) links the coal intensity change to total factor productivity change in the plants (Färe et al., 1994). The last two components measure the effects on coal intensity change from the change in capital-coal ratio and the change in labor-coal ratio, respectively. If $k_\tau \leq (\geq) k_t$, then $KC \geq (\leq) 1$, which suggests that an increase in capital-coal ratio will not increase the potential coal intensity of electricity generation. Similarly, $LC \geq (\leq)$ 1 if $l_\tau \leq (\geq) l_t$, which results from the substitution between labor and coal in the production process of the plants.

4. Results

We apply the decomposition framework to the constructed dataset for Chinese coal-fired power firms covering two years (2009 and 2012). This section summarizes the results of the decomposition exercises, heterogeneity analyses, and robustness checks.

4.1. Decomposition results

To obtain the desired decomposition results in (5), we need to construct the production frontiers for coal-fired power plants in the years 2009 and 2012.[15] The production frontiers are constructed by using data envelopment analysis (Charnes et al., 1978). As described earlier, our constructed data for year 2009 included 483 firms, while only 389 of them were still in the 2012 sample. For obvious reasons, we use the 483 firms when constructing production frontier for year 2009. We have 532 firms for constructing the 2012 production frontier. From constructing the frontier for the year 2009, we find that firms being on or closer to production frontier have the following characteristics: they are in eastern regions, state-owned, and large.[16]

Fig. 2 plots the distributions of technical efficiency score across the 389 common firms in the two years of 2009 and 2012. We observe large technical inefficiencies for many firms in both years. This finding is in line with Wei et al. (2013). Overall, the probability mass shifted towards the right from 2009 to 2012. The mode of the distribution also shifted to the right. That is, the figure shows a significant improvement in technical efficiency (i.e., technological catch-up) for the plants over this period. It implies that the sampled firms, on average, used their coal and other inputs in a more efficient way to generate electricity in 2012 in comparison to 2009.

With the constructed production frontiers and data on inputs and output, each component of the decomposition (5) for every firm can be computed.[17] Table 2 reports the geometric means of contributions to coal intensity change stemmed from the four sources: technological catch-up [$(EFF - 1) \times 100$], technological progress [$(TECH - 1) \times 100$], change in capital-coal ratio [$(KC - 1) \times 100$], and change in labor-coal ratio [$(LC - 1) \times 100$].

The first row in Table 2 summarizes the decomposed results for the period from 2009 to 2012. We report the geometric means of the coal intensity, the coal intensity change between the two years, and the decomposed components of the change for the common 389 firms. The firms, on average, used 346.45 *gce* of coal for producing 1 kWh of electricity in 2009. The coal intensity decreased by 2.76% and reached to 336.87 *gce* per kWh in 2012. The decomposition results suggest that the improvement in technical efficiency (i.e., a negative value for the "technological catch-up" component in Table 2), on average, was the major reason for mean decrease of national coal intensity for electricity generation in our sample. Had all firms produced electricity in 2012 as technically efficient as year 2009, the 2012 intensity could have been 347.87 *gce* per kWh, which is 3.26% higher than the actual 2012 level. Considering the huge amount of coal burned by the plants, the technological catch-up contributes significantly to limit coal consumption in the sector. The results also indicate the contribution from capital accumulation to lowering coal intensity is −0.76%.

We rearrange the firms into two groups: the "increasing CI" group includes the firms which had higher coal intensity in year 2012 than 2009; the "decreasing CI" group includes the firms with lower intensity in 2012 than 2009. The geometric means of the coal intensity for the firms in each group are reported in rows 2 and 3 of Table 2, respectively. Comparing the results for the two groups, we note that the main reason for the difference in the trend of coal intensity change is that the two groups have a large gap in technological catch-up over the years. This

[15] We use OnFront to construct the production frontiers and calculate the decomposition components.

[16] Later in the section, we classify the firms into three size categories (i.e., small, medium, and large) based on their capital stock.

[17] These intermediate results are available from the authors upon request. To calculate the values for the factors in the components, we note that output distance function is reciprocal to the output-based Farrell measure of efficiency (Farrell, 1957). The values can be obtained by solving linear programming problems, see Färe et al. (1994) and Wang (2007) for details.

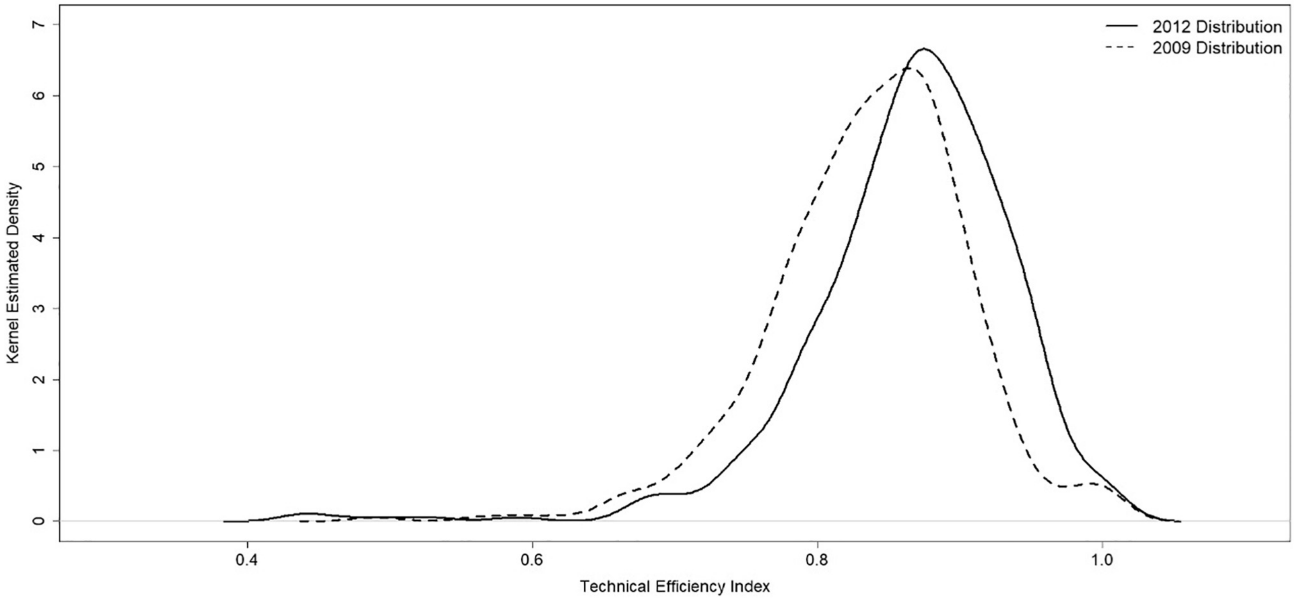

Fig. 2. Distribution of technical efficiency index in 2009 and 2012.

Table 2
Decomposition results: Geometric means.

	N	Coal intensity			Contribution to CI change (%)			
		2009	2012	Change (%)	Technological catch-up	Technological progress	Change in k-c ratio	Change in l-c ratio
All firms	389	346.45	336.87	−2.76	−3.16	1.11	−0.76	0.07
Increasing CI	72	337.02	360.49	6.96	5.52	2.04	−0.50	−0.16
Decreasing CI	317	348.63	331.73	−4.85	−5.03	0.90	−0.82	0.12

Note: "Increasing CI" group includes all firms which have higher coal intensity in year 2012 than their own intensity in 2009; "Decreasing CI" for firms with lower intensity in 2012.

Table 3
Decomposition results by regions: 2009–2012.

Region	N	Coal intensity			Contribution to CI change (%)			
		2009	2012	Change (%)	Technological catch-up	Technological progress	Change in k-c ratio	Change in l-c ratio
East	166	341.44	332.30	−2.68	−2.78	1.25	−1.31	0.18
Central	142	343.89	330.67	−3.84	−4.14	0.87	−0.59	0.03
West	81	361.62	357.91	−1.03	−2.23	1.22	0.09	−0.08

Note: The criteria for classifying provinces into three different regions are obtained from public document from the government. The eastern region includes: Liaoning, Hebei, Tianjin, Beijing, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan, Guangxi. The central region includes: Heilongjiang, Jilin, Inner Mongolia, Shanxi, Anhui, Jiangxi, Hunan, Hubei, Henan. The western region includes: Chongqing, Sichuan, Yunnan, Guizhou, Shaanxi, Qinghai, Gansu, Ningxia, Xinjiang, Tibet.

factor solely constitutes about 89%[18] of the difference in coal intensity change between the two groups.

4.2. Heterogeneity

In this subsection, we investigate the possible heterogeneity of the estimated results reported in the previous subsection. This will allow us to not only check the validity of the reported results, but also investigate whether the impacts from the four sources varied across groups of the power plants of different characteristics.

In the first heterogeneity analysis, we group the firms by their locations: eastern, central, and western regions. More than 40% of the firms in our 2009–2012 comparison sample are located in the affluent eastern region of the country. Table 3 reports the mean changes in coal intensity and the impacts of the four components for these three regions.

The results suggest that technological catch-up induced coal intensity of the firms in all regions to decrease during the period from 2009 to 2012. The central region experienced the largest impact from this factor on reducing coal intensity over the years. We also find that capital accumulation contributed to reducing coal intensity in the eastern and central regions. This confirms the previous finding from analysis on the whole sample reported in Table 2. Firms in the western region had the highest level of coal intensity and it decreased at a relatively lower speed in comparison to other regions over the years. The difference in technological catch-up among the three regions can largely explain the gap in the coal intensity change among them over the period.

As the second heterogeneity analysis, Table 4 reports the decomposition results for firms of different sizes (i.e., small, medium, and large)[19] in 2009. The results indicate that small firms had relatively high level of

[18] The number is calculated in the following way: $(-5.03–5.52) / (-4.85–6.96) * 100\% = 89\%$.

[19] Size category here is defined by the product of generation capacity and hours of operation. We also use number of employees to define size and obtain qualitatively the same decomposition results.

Table 4
Decomposition results by size: 2009–2012.

Capital	N	Coal intensity			Contribution to CI change (%)			
		2009	2012	Change (%)	Technological catch-up	Technological progress	Change in k-c ratio	Change in l-c ratio
Small: Capital ≤ 2475	130	370.54	354.00	−4.46	−4.71	2.37	−1.93	−0.14
Medium: 2475 ≤ Capital ≤ 4905	130	340.59	334.04	−1.92	−2.51	0.68	−0.18	0.10
Large: Capital ≥ 4905	129	329.37	323.19	−1.88	−2.24	0.28	−0.14	0.24

Note: Size category here is defined by the product of generation capacity and hours of operation. Based on the product, we classify the firms into three groups with equal number of firms.

coal intensity in both years. However, their coal intensity declined much faster than other firms. As for the contributing factors, technological catch-up is again the most influential one for decreasing coal intensity over the years for all three size groups. For smaller firms, coal intensity declined by about 4.46%, while technological catch-up in these firms decreased the coal intensity by 4.71%. Both the scores of technological catch-up and the change in capital-coal ratio reported in Table 4 reveal the importance of the size of coal-fired power plants in decreasing coal intensity of electricity generation.

In the third heterogeneity analysis, we focus on different types of ownership. From Table 5, we find that state-owned plants perform relatively better in technological catch-up over the years. A possible explanation is that private owned firms are exposed to environmental regulations (e.g., those on SO2 emissions) differently (Hering and Poncet, 2014). The table also indicates that non-SOE domestic firms and foreign invested firms performed better in terms of the effect from changes in capital-coal ratio. Again, difference in technological catch-up among the two ownership groups can solely explain their gap in changes in coal intensity over the period.

4.3. Robustness checks

This subsection checks the robustness of the main results presented in Table 2. First, we exclude some outliers from the previously constructed sample. An observation is deleted if it belongs to a firm whose capital in 2009 was either greater than the 95th percentile or less than the 5th percentile. This practice leaves us with 351 firms for the 2009–2012 comparison sample. The geometric means for the related measures are reported in the first row of Table 6. Again, the results suggest that technological catch-up is the major factor for lowering coal intensity over the years.

Second, we exclude outliers which are defined using coal consumption. That is, an observation is deleted from the sample if it belongs to a firm whose coal consumption was greater than the 95th percentile or less than the 5th percentile. The third check excludes some outliers based on wage payment. The results from the two additional checks are reported in rows 2 and 3 of Table 6. Both checks confirm the importance of technological catch-up in reducing coal intensity.

5. Distribution analysis

We note that the preceding interpretations about the contributions of the four components to changes in coal intensity are based on mean values. To give more information, this section aims to explore the relative importance of each of the four decomposition components to changes in the distribution of coal intensity over the time period. To do so, we follow the previous studies on labor productivity (Kumar and Russell, 2002; Henderson and Russell, 2005) and on energy intensity (Wang, 2013).

We rewrite the decomposition (5) for coal intensity change between the years of 2009 and 2012 as follows:

$$CI_{2012} = CI_{2009} \times EFF \times TECH \times KC \times LC.$$

This equation shows that the coal intensity in 2012 can be constructed by successively multiplying coal intensity in 2009 by each of the four components from the decomposition exercise. To isolate the effect on the distribution dynamics of coal intensity from the change in labor-coal ratio only, we examine the counterfactual 2012 coal intensity distribution of the variable

$$CI^L = CI_{2009} * LC,$$

which assumes that there is no change in capital-coal ratio, technological change, or technological catch-up between the two years. Panel (A) of Fig. 3 shows the counterfactual distribution. For the purpose of making comparisons, the panel also presents the actual distributions in 2009 and 2012. If the labor-coal ratio did not change for any firm, the counterfactual distribution would be identical to the actual 2009 distribution. Panel (A) indicates that the counterfactual 2012 distribution and the

Table 5
Decomposition results by ownership: 2009–2012.

Ownership	N	Coal intensity			Contribution to CI change (%)			
		2009	2012	Change (%)	Technological catch-up	Technological progress	Change in k-c ratio	Change in l-c ratio
SOE	330	345.63	335.89	−2.82	−3.29	0.92	−0.49	0.07
Non-SOE	59	350.43	346.04	−1.25	−1.38	2.18	−2.11	0.10

Note: SOE refers to state-owned enterprises.

Table 6
Robustness checks: 2009–2012.

Excluding outliers	N	Coal intensity			Contribution to CI change (%)			
		2009	2012	Change (%)	Technological catch-up	Technological progress	Change in k-c ratio	Change in l-c ratio
Capital	351	345.24	335.23	−2.90	−3.31	0.96	−0.53	0.00
Coal consumption	351	345.04	335.24	−2.84	−2.84	1.14	−0.77	−0.02
Wage payment	351	345.62	335.81	−2.84	−3.21	0.97	−0.61	0.03

Note: In the rows of this table we remove the firms whose capital stock, coal consumption, and wage payment, respectively, are less than the 5th percentile or more than the 95th percentile and repeat the decomposition analysis again.

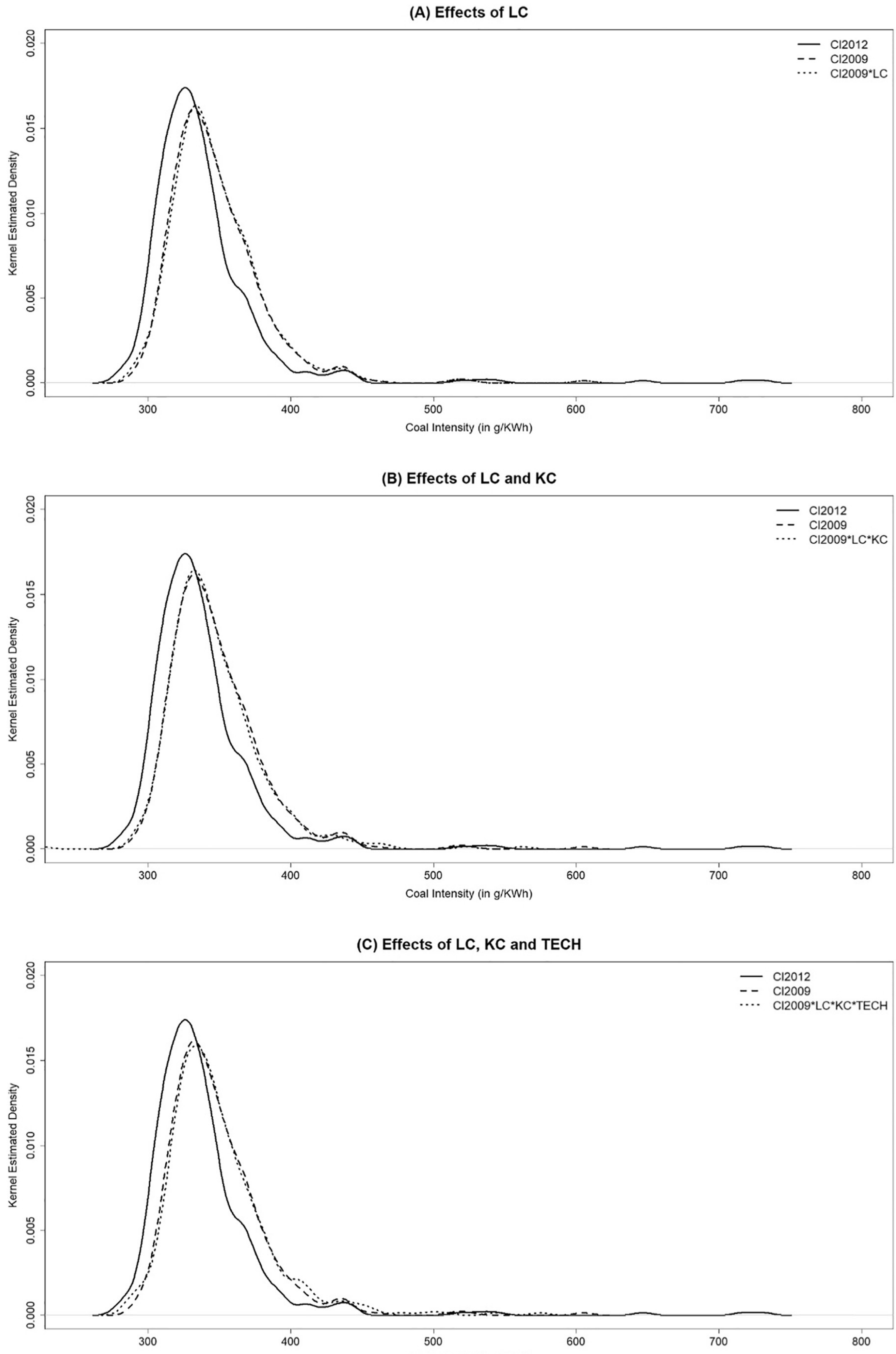

Fig. 3. Counterfactual distributions of coal intensity. Sequence of including effects of decomposition: *LC* (change in labor-coal ratio), *KC* (change in capital-coal ratio), and *TECH* (technological progress).

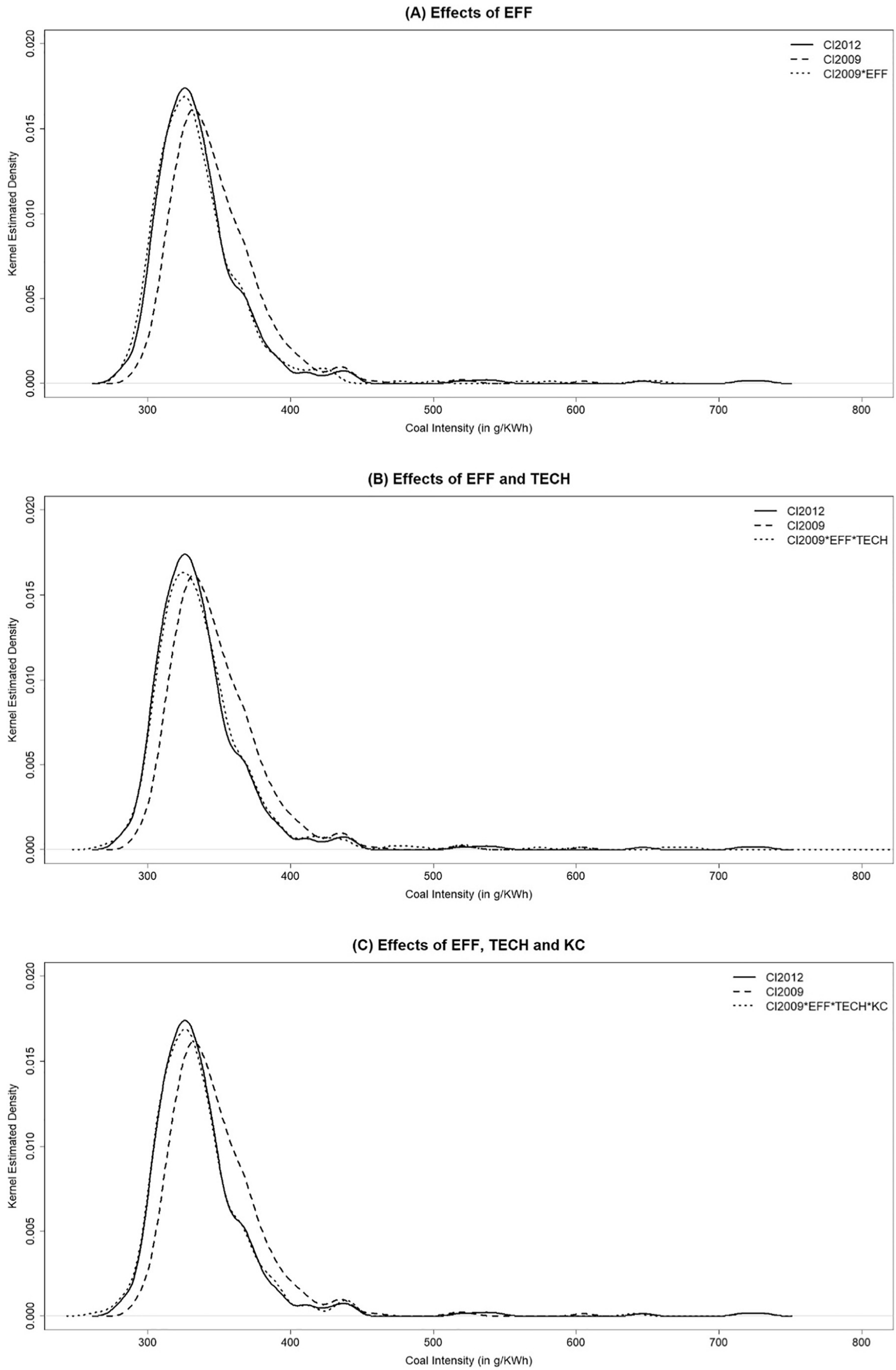

Fig. 4. Counterfactual distributions of coal intensity. Sequence of including effects of decomposition: *EFF* (technological catch-up), *TECH* (technological progress), and *KC* (change in capital-coal ratio).

2009 actual distribution are very close to each other. However, the counterfactual distribution is different from the 2012 actual distribution. This suggests that the change in labor-coal ratio played a negligible role in moving the 2009 distribution to the 2012 actual distribution of coal intensity.

Now considering the additional effect from the change in capital-coal ratio, Panel (B) of Fig. 3 draws the counterfactual distribution of the following variable:

$$CI^{KL} = CI_{2009} \times LC \times KC = CI^{L} \times KC,$$

which shows the joint effect of changes in labor-coal ratio and capital-coal ratio on moving the 2009 distribution. Obviously, the effect from the change in capital-coal ratio also played a minor role in changing the distribution of the coal intensity over the years. The additional effect of technological progress can be observed by the counterfactual distribution of the variable

$$CI^{TKL} = CI_{2009} \times TECH \times KC \times LC = CI^{KL} \times TECH.$$

Panel (C) of Fig. 3 suggests that the new distribution is almost identical to the previous ones and the 2009 actual distribution.

If we further add the impact of technological catch-up, the resulting distribution would be the actual 2012 distribution.[20] This suggests that changes of the counterfactual distribution are profound if the impact of technological catch-up is included. It provides evidence that technological catch-up is the primary driving force in changing the distribution of coal intensity.

The above graphical analysis introduces the four decomposition components in an arbitrary order. If we change the order, the general result is the same: change in the shape of the distribution from 2009 to 2012 is mainly caused by technological catch-up.[21] Panel (A) of Fig. 4 provides perhaps the most convincing supporting evidence. This shows that the technological catch-up solely moves the 2009 distribution much closer to the 2012 actual distribution. Furthermore, including any other decomposition component does not significantly change the distribution.

The above analysis on coal intensity distribution dynamics by using figures can be complemented by a formal test for the statistical significance of differences between the actual 2012 distribution and counterfactual distributions. It indirectly tests for the statistical significance of the relative contributions of the four components of the decomposition of coal intensity changes to changes in the distribution of coal intensity. Table 7 reports the test results for the null hypothesis that the actual distribution in 2012 and the counterfactual distributions generated by sequential introduction of four components of the decomposition (5) are identical. To compare the distributions, we use the statistic proposed by Li (1996) and implement a specific bootstrap procedure (Li, 1999) to obtain the critical value of the statistic.[22]

The first row in Table 7 indicates that the actual distributions in 2009 and 2012 are significantly different at 1% significance level, confirming Fig. 1 presented earlier. The next four tests compare the actual distribution in 2012 with the counterfactual distributions, assuming that every counterfactual distribution is based on only one decomposing component. Row 2 suggests that we are unable to reject the hypothesis that the actual 2012 distribution is identical to the counterfactual distribution incorporating only technological catch-up. This confirms the previous finding that this factor alone can explain the overall change in the distribution of coal intensity from 2009 to 2012, shown in Panel (A) of Fig. 4. However, rows 3–5 of Table 7 find that introducing any of the other three decomposition components solely does not generate similar statistical testing result. Furthermore, statistical tests reported in the rows 6–11 of Table 7 compare the 2012 actual distribution with the counterfactual distributions, assuming that two of the four components are included in each counterfactual distribution. Finally, statistical tests reported in rows 12–15 compare the counterfactual distributions with the inclusion of the effects from three of the four components with the actual 2012 distribution.

Table 7
Distribution hypothesis tests.

Null hypothesis H_0	t-Test statistics	Bootstrap p-value	Conclusion of testing H_0
1. $f(CI_{2012}) = g(CI_{2009})$	7.2247	0.0000	Reject
2. $f(CI_{2012}) = g(CI_{2009} * EFF)$	−0.0602	0.9393	Fail to reject
3. $f(CI_{2012}) = g(CI_{2009} * TECH)$	9.8758	0.0000	Reject
4. $f(CI_{2012}) = g(CI_{2009} * KC)$	5.9167	0.0007	Reject
5. $f(CI_{2012}) = g(CI_{2009} * LC)$	8.5369	0.0000	Reject
6. $f(CI_{2012}) = g(CI_{2009} * EFF * TECH)$	0.0197	0.9853	Fail to reject
7. $f(CI_{2012}) = g(CI_{2009} * EFF * KC)$	0.2346	0.7670	Fail to reject
8. $f(CI_{2012}) = g(CI_{2009} * EFF * LC)$	−0.1447	0.8603	Fail to reject
9. $f(CI_{2012}) = g(CI_{2009} * TECH * KC)$	7.8310	0.0000	Reject
10. $f(CI_{2012}) = g(CI_{2009} * TECH * LC)$	10.9590	0.0000	Reject
11. $f(CI_{2012}) = g(CI_{2009} * KC * LC)$	6.8971	0.0000	Reject
12. $f(CI_{2012}) = g(CI_{2009} * EFF * TECH * KC)$	−0.0245	0.9763	Fail to reject
13. $f(CI_{2012}) = g(CI_{2009} * EFF * TECH * LC)$	0.0448	0.9580	Fail to reject
14. $f(CI_{2012}) = g(CI_{2009} * EFF * KC * LC)$	0.0296	0.9723	Fail to reject
15. $f(CI_{2012}) = g(CI_{2009} * TECH * KC * LC)$	8.7372	0.0000	Reject

Note: $f(CI_{2012})$ is the actual coal intensity distribution in 2012, and $g(\cdot)$ is the counterfactual coal intensity distribution in 2012 that is obtained by incorporating different combinations of the four decomposition components (EFF, TECH, KC, and LC) into the coal intensity distribution in 2009. Further, the test statistic used here is based on Li (1996, 1999).

As shown in Table 7, the actual 2012 distribution is statistically different from any resulting counterfactual distribution if the effect from technological catch-up is not included. However, if technological catch-up is included in the counterfactual distribution, for any combination of two or three decomposition components, the tests would suggest that the resulting counterfactual distribution and the actual 2012 distribution are not statistically different from each other. In sum, the testing results reported in Table 7 also confirm that technological catch-up is the major driving force for the coal intensity change in China's coal-fired power plants between 2009 and 2012.

6. Concluding remarks

Coal-fired power industry is the largest consumer of coal in China. Many firms in this industry have a great potential to lowering their coal intensity of electricity generation. Data suggest that the absolute level and change rate of coal intensity varied significantly across power plants from 2009 to 2012. To understand the dynamics of the coal intensity change, this paper decomposed changes in coal intensity of net electricity generation across coal-fired power plants between the years 2009 and 2012 into four components: technological catch-up, technological growth, change in capital-coal ratio, and change in labor-coal ratio. We found that mainly technological catch-up decreased the mean coal intensity of electricity generation in the coal-fired power plants during the period of the study. It was also the main driver for the heterogeneity in coal intensity changes across different groups of the plants.

Though the study do not provide explanations about fundamental drivers of coal intensity change, it is useful to identify the plants that are technically inefficient in producing electricity. The results imply that policy interventions should focus more on improving technical efficiency of firms in terms of using input factors like coal. Our work suggests that the small firms that located in the western region of the country are the best candidates for efficiency relevant policy intervention.

[20] The actual 2012 distribution is shown in Figs. 3 and 4.

[21] Figures for other counterfactual distributions are available from the authors upon request.

[22] For more details on the procedures for implementing the test, see Henderson and Russell (2005), Kumar and Russell (2002), and Wang (2013).

The present study could be extended in the future in different ways when more data become available. First, we could check if the main results hold for other time periods. Second, the decomposition framework adopted in the present paper can be extended if any undesired output (e.g. sulfur dioxide, carbon dioxide, and other pollutants) is considered. One way to incorporate additional outputs is to utilize similar frameworks from the literature (see, e.g., Färe et al., 2001; Zhou and Ang, 2008) which estimate distance functions in multi-output cases.

Appendix A. More details on the decomposition framework

The appendix draws heavily on Wang (2013). Definition (2) suggests that $D_o^\tau(K_t,L_t,C_t,\alpha E_t) = \alpha D_o^\tau(K_t,L_t,C_t,E_t)$ where α is a positive scalar. Using production technology in year t as a reference, we write the coal intensity change between years t and τ as,

$$\frac{C_\tau/E_\tau}{C_t/E_t} = \frac{D_o^t(K_t,L_t,C_t,E_t)}{D_o^\tau(K_\tau,L_\tau,C_\tau,E_\tau)} \times \frac{D_o^\tau(K_\tau,L_\tau,C_\tau,E_\tau)}{D_o^t(K_\tau,L_\tau,C_\tau,E_\tau)} \times \frac{\frac{D_o^t(K_\tau,L_\tau,C_\tau,E_\tau)}{E_\tau}\times C_\tau}{\frac{D_o^t(K_t,L_t,C_t,E_t)}{E_t}\times C_t}$$
$$= \frac{D_o^t(K_t,L_t,C_t,E_t)}{D_o^\tau(K_\tau,L_\tau,C_\tau,E_\tau)} \times \frac{D_o^\tau(K_\tau,L_\tau,C_\tau,E_\tau)}{D_o^t(K_\tau,L_\tau,C_\tau,E_\tau)} \times \frac{D_o^t(K_\tau,L_\tau,C_\tau,1)\times C_\tau}{D_o^t(K_t,L_t,C_t,1)\times C_t}. \quad (A.1)$$

In (A.1) and hereafter, output distance functions with respect to two different time periods are defined in similar ways. For instance,

$$D_o^\tau(K_t,L_t,C_t,E_t) = \inf\{\theta : (K_t,L_t,C_t,E_t/\theta) \in S^\tau\}.$$

Definition for output distance function in (2) indicates that $\frac{E_t}{D_o^t(K_t,L_t,C_t,E_t)}$ (i.e., $\frac{1}{D_o^t(K_t,L_t,C_t,1)}$) represents the maximum potential amount of electricity generated when the production technology is S^t and the input bundle is (K_t,L_t,C_t). Thus, $\frac{D_o^t(K_\tau,L_\tau,C_\tau,1)\times C_\tau}{D_o^t(K_t,L_t,C_t,1)\times C_t}$ measures the change in minimum potential coal intensity during the two periods by using the technology S^t as a reference. With the assumption that the production technology is constant-returns-to-scale (Färe, 1988), we have $D_o^\tau(\beta K_t, \beta L_t,\beta C_t,\beta E_t) = \beta^{-1}D_o^\tau(K_t,L_t,C_t,E_t)$ where β is a positive scalar. Thus, Eq. (A.1) can be rewritten as

$$\frac{C_\tau/E_\tau}{C_t/E_t} = \frac{D_o^t(K_t,L_t,C_t,E_t)}{D_o^\tau(K_\tau,L_\tau,C_\tau,E_\tau)} \times \frac{D_o^\tau(K_\tau,L_\tau,C_\tau,E_\tau)}{D_o^t(K_\tau,L_\tau,C_\tau,E_\tau)} \times \frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_t,l_t,1,1)}$$
$$\equiv EFF \times TECH(\tau) \times PCI^t, \quad (A.2)$$

where $k_t \equiv K_t/C_t$ and $l_t \equiv L_t/C_t$.

The third component in (A.2), PCI^t, measures the change in potential coal intensity. Its value depends on changes between time periods t and τ in: 1) capital-coal ratio from k_t to k_τ, and 2) labor-coal ratio from l_t to l_τ. To isolate the two effects on PCI^t, we further decompose it in the following ways:

$$\frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_t,l_t,1,1)} = \frac{D_o^t(k_\tau,l_t,1,1)}{D_o^t(k_t,l_t,1,1)} \times \frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_\tau,l_t,1,1)}$$

or

$$\frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_t,l_t,1,1)} = \frac{D_o^t(k_t,l_\tau,1,1)}{D_o^t(k_t,l_t,1,1)} \times \frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_t,l_\tau,1,1)}.$$

To avoid the ambiguity of choosing one from the two preceding, we take the geometric mean of them and rearrange it in the following equation:

$$PCI^t = \frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_t,l_t,1,1)} = \left\{\frac{D_o^t(k_\tau,l_t,1,1)}{D_o^t(k_t,l_t,1,1)} \times \frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_\tau,l_t,1,1)}\right\}^{\frac{1}{2}}$$
$$\times \left\{\frac{D_o^t(k_t,l_\tau,1,1)}{D_o^t(k_t,l_t,1,1)} \times \frac{D_o^t(k_\tau,l_\tau,1,1)}{D_o^t(k_t,l_\tau,1,1)}\right\}^{\frac{1}{2}} \equiv KC^t \times LC^t, \quad (A.3)$$

where the first term shows the effect when only capital-coal ratio changes between two time periods. The second term measures the effect of the change in labor-coal raio solely.

Combining (A.2) and (A.3), we obtain that

$$\frac{C_\tau/E_\tau}{C_t/E_t} = EFF \times TECH(\tau) \times KC^t \times LC^t. \quad (A.4)$$

If we use production technology in time period τ as a reference, analogs to (A.1)–(A.4) can be easily obtained.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.01.032.

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