Does Energy Efficiency Improvement Regulation Backfire?
——Evidence From 'Top 1000 Firms Energy Saving Program'

Yue Xu, Xiaolan Chen*

School of Economics, Sichuan University, Chengdu, China

Abstract

Improving energy efficiency plays vital role for navigating the energy crisis, mitigating air emission and realizing climate goals. China initiated a target-based energy conservation regulation- the Top 1000 Firms Energy Saving Program(T1000P)-aiming to decrease energy intensity in its eleventh Five Year Plan. Leveraging non-radial directional distance function (NDDF) framework and Propensity Score Matching-Difference in Difference (PSM-DID) strategy, we investigate the effect of T1000P on firm energy efficiency in China from 2002-2010. We find the T1000P have negative effect on energy efficiency of participants. The finding indicates that the inhibition effect tends to be pronounced for state-owned firms, firms in poor resource regions. In addition, this study finds that T1000P causes factor reallocation within firm and inhibits the firm innovation. This study provides timely policy implications by shedding light on the effect of such a command-and-control environmental regulation on firm efficiency.

Keywords: Top 1000 Firm Energy Saving Program; Command-and-control environmental regulation, Energy efficiency; Factor reallocation; Inhibition effect

1.Introduction

To address the energy crisis, focusing on energy efficiency action is the unambiguous first and best response to simultaneously meet affordability, supply security and climate goals(IEA, 2022). China is a major energy consumer and CO2 emitter in the world, and China pledge to achieve carbon peek before 2030 and carbon neutrality before 2060. China has attached great importance to high-quality sustainable development(ICCSD Tsinghua University, 2022), the central government has initiated several guidelines and regulations to reduce to energy consumption(Zhou et al., 2010). The T1000P, one of crucial energy conservation regulation to achieve 11FYP ambitious goal, targets the largest energy-intensive enterprises. An extensive literature mainly focuses on the whether the targets are achieved and the induced effects on specific industries, leaving the impact on firm energy efficiency unexplored. This study will fill the gap and investigate how the T1000P, aiming to improve energy efficiency, affects energy efficiency in firm-level.

The central concern of the studies is whether environmental regulation can improve energy efficiency. The existing studies finds that the relationship between environmental regulation and energy efficiency remains controversial, one side argue that environmental regulation can improve energy efficiency, but other side points out that environmental regulation may inhibit the energy efficiency. The mixed conclusion about the relationship between environmental regulation and energy efficiency often lies in the different type and intensity of the regulation(Bu et al., 2022). Studies focus on the effects of the T1000P mainly at industrial level or firms in several industries(Filippini et al., 2020; Shao et al., 2019), but evidence including all targeted industries remain scarce. Moreover, Previous studies mainly use energy intensity as the proxy of energy efficiency, ignoring the mutual substitution and structural changes among different factors of production, which may amplify the impact of energy inputs on economic output(Hu and Wang, 2006).

The debates about the effect of the environmental regulation on energy efficiency mainly focus on two theories. Compliance cost theory holds that environmental regulation would increase enterprise costs, which is equivalent to imposing new constrains on the enterprise's production decision harming firm competitiveness. Besides, the compulsory regulation might have a crowding-out effect on R&D investment, which create corporate cost expenditures and inhibits corporate energy efficiency(Boyd and McClelland, 1999; Gollop and Roberts, 1983; Gray, 1987). According to the Porter's hypothesis, conversely, environmental regulation triggers corporate to conduct innovation and ultimately improves productivity, called innovation offsets(Curtis and Lee, 2019; Porter and Linde, 1995).

Unprecedently, the 11th Five Year Plan(2006-2010) sets an ambitious target of reducing energy intensity by 20%. The T1000P is central government assign compulsory energy saving targets for almost 1000 energy-intensive firms. The calculation method of energy saving target[1] hinges on how much the considered firm could lower their energy intensity, it is essence an intensity standard(Xiao et al., 2023). However, firms may achieve their target by improving their technology(Shao et al., 2019), diluting energy-intensity by production expansion(Zhao et al., 2016), shifting energy-intensive production to unregulated firm in the same conglomerate(Chen et al., 2021), even by manipulating data to exaggerate performance(Karplus et al., 2020). Although many scholars remain interest in this policy, there is no study carefully analyzing how the T1000P, the first initiative to improve firm energy efficiency, impacts the firm energy efficiency.

In this study, we use DEA method to estimate firm energy efficiency, and investigate the impact of the T1000P on energy efficiency in firm level. This study attempts to make marginal contributions in the following three aspects. Firstly, distinct from the previous studies that measured energy efficiency based on single factor energy efficiency, this study adapts non-radial directional distance function (NDDF) using DEA method to estimate firm energy efficiency in all targeted industries(266,254 firms). This model fully considers various input factors and undesirable output. Thus, it can exhaustively portray the energy efficiency, and fill the deficiency of energy efficiency estimation and analysis in micro-firm level. Secondly, we employ Propensity Score Matching method to identify the pairs for participants in the T1000P, and use different-in-difference approach to identify the effect of the T1000P on firm energy efficiency. This study reveals the aftermath of the T1000P, that the compulsory energy saving regulation significantly inhibits the firm energy efficiency, supporting conclusive empirical evidence on compliance theory. It supplements literature examining the effects of environmental regulations on firm energy efficiency. As a supplement, our study further explores the heterogeneous effects, the possible influencing mechanism form resource reallocation and innovation. The finding indicates the T1000P cause factor reallocation within firm and have adverse effect on firm innovation. Moreover, nations are implementing various programs to reduce carbon emissions and improve energy efficiency in response to widespread concerns about climate change(Tanaka, 2011). This study has far-reaching significance for optimizing the design of such regulations.

This study is organized as follows. Section 2 introduces the background of the T1000P and reviews relevant literature. Section 3 evaluates the indicators chosen for measuring energy efficiency proximity and provides the details on estimation strategy. Section 4 shows the empirical results and further discussion on mechanism. Section 5 draws conclusions and illustrates the policy implications.

[1] The energy saving target is denoted as: $S_t = Y_t \times (Intensity_t - Intensity_{t-1})$, t is year, S denotes energy saving, Y is output, $Intensity$ is firm energy intensity, which is measured by energy consumption divided by output.

2.Background

2.1The “Top 1000” Program

After China accession to the WTO in 2001 leading to economy take off, the soaring energy demand growth from 2002 to 2005 reveals the inadequacy of previous energy conservation regulations(Zhou et al., 2010). The T1000P was established during 11 FYP(2006-2010) and target 1008 industrial firms[2] with energy consumption above 180,000 tce[3] in 2004, accounting for 47% of China's industrial energy consumption and 33% of total energy consumption. Those firms belong to 9 energy-intensive sectors: coal, textile, paper, chemical, petroleum and petrochemicals, building materials, iron and steel, non-ferrous metal, and power and heat. In terms of energy structure, these firms utilized coal, crude oil, coke, natural gas for 67.79% of the total energy consumed in 2006, and the remaining 32.21% was made up of electricity, heat, and other energy sources.

The program had two stated goals: to significant increase the energy efficiency of these large enterprises and to save 100 million tce in energy consumption by 2011. The T1000P was modeled on international target-setting programs called voluntary or negotiated agreement programs. The central government set mandatory energy savings targets for these enterprises as the primary quantitative indicator of their energy saving performance. The targets were not based on detailed assessments of energy-savings potential of each firms, and given the time pressure and large number of participant firms it is not set targets for those firms based on the potential saving identified(Price et al., 2010). As mentioned above, the firm could “achieve compliance” with a marginal improvement in energy intensity or though other methods. Various measures were imposed on targeted firms including linking energy saving targets to promotion of local officials and leaders in state-own or state-controlled firms. The energy-saving authorities of the province oversee and monitor firms in their energy management, energy auditing, and energy inspections. Non-compliance firms are subject to a deadline for rectification and suspension the high-energy consumption project. Additionally, support measures for non-compliance firms such as exemptions from national inspections, investment on high-energy consumption projects, and new industrial land are not granted approval. Therefore, the T1000P follow a command-and-control approach, which differs from the Climate Change Agreement in the U.K. or the Keidanren Voluntary Action Plan in Japan, where the energy-reduction goal is more of a voluntary commitment based on detailed assessment by company or independent third party and government-business negotiation(Price et al., 2010; Xiao et al., 2023).

According to the communique of the T1000P reported by NDRC, energy saving targets of firms were all overachieved, achieving 1.65 million tce in energy saving. Among the 881 firms evaluated at end of the T1000P, there were 866 firms meet the targets. Considering the T1000P can be effective in fulfilling energy saving target, the T1000 was upgraded to the Top 10000 Firm Energy Saving and Low-carbon Program(T10000P) during 12 FYP(2011-2015), that broadens the coverage of firms.

2.2Literature review

As nations attach importance to improving energy efficiency, many scholars pay attention to the energy efficiency of the regional, industries and firms. Patterson(1996) suggests energy efficiency refers to using less

[2] Firms originally included in the program but closure, bankruptcies, mergers, or other major changes in production would be exclude from the annual communique of National Development and Reform Commission(NDRC). Therefore, there are 953, 922, 901, 881 firms were reported by NDRC for year 2007, 2008, 2009, 2010, respectively.
[3] tons of coal equivalent (tce)

energy to produce the same amount of services or useful output. There are two main indicators to measure energy efficiency: Singal factor energy efficiency and Total factor energy efficiency. Singal factor energy efficiency is broadly defined using energy consumption intensity. It is energy consumption per unit of GDP without considering other factors of production and mutual substitution and structural changes among different factors of production. It may amplify the impact of energy inputs on economic output(Hu and Wang, 2006). And estimating energy efficiency ignores undesirable output could result in biased estimates(Mandal, 2010). In contract, total factor energy efficiency, which is usually measured using SFA and DEA, and takes into account other inputs such as capital and labor in addition to energy. Compared with SFA, DEA is more suitable for efficiency measurement with multiple inputs and multiple outputs(Shi et al., 2010). Shephard distance function and Directional distance function(DDF)(Chambers et al., 1998, 1996) are used as distance function in DEA method. Shephard distance function does not credit reduction of undesirable output, since all outputs are expended at same rate. DDF is more widely use in energy and environmental efficiency studies because it is capable of expanding desirable outputs and contracting energy inputs or bad outputs simultaneously(Zhang and Choi, 2014). However, when some slack exits DDF, reducing undesirable outputs (inputs) and increases desirable outputs at the same rate, may overestimate efficiency. Then, non-radial DDF (NDDF) is developed by incorporating slacks into efficiency(Färe and Grosskopf, 2010; Fukuyama and Weber, 2009). Hu and Wang(2006) defines ratio of potential energy consumption to actual energy consumption as proxy of energy efficiency, Zhou and Ang(2008), Choi et al.(2012) employe the formula in different models. Zhou(2012) define energy performance index (EPI)as the ratio of actual energy efficiency to potential energy efficiency using NDDF approach. The index was widely used to estimate energy efficiency(Cheng et al., 2020; Guo et al., 2023; Peng et al., 2022; Qu et al., 2020; Zhang et al., 2014). To estimate the dynamic change and driving factors of productivity progress many studies used Malmquist–Luenberger index (MLI)(Oh and Lee, 2010; Zhang et al., 2022). Since heterogeneity across the groups might lead to a different production technology, group frontier and meta-frontier are employed to make efficiency across groups comparable(Chiu et al., 2012; Oh and Lee, 2010; Zhang et al., 2013).

Previous studies about effect of environmental regulation on energy efficiency mainly use energy intensity as the proxy of energy efficiency, and energy efficiency estimated in different studies adopt various models in different context, which results in divergent conclusion and policy implication. Some studies show that command-and-control environmental regulation has negative effect on energy efficiency by power cuts and production restriction, making firms shift electric production to low efficient off-site utilities(Curtis and Lee, 2019; Shi et al., 2022). Others argue it can improve energy efficiency by optimizing energy consumption structure, promoting firm innovation(Chen et al., 2020; Guo et al., 2023; Lyu et al., 2022). Some studies discover environmental regulation cause nonlinear effect on energy efficiency(Xu and Xu, 2022). Wu et al.(2020) discover a positive U-shaped relationship between environmental regulations and energy efficiency. Besides, some papers point out the market regulation can improve energy efficiency better than the command-and-control regulation(Curtis and Lee, 2019; Li et al., 2021; Wang et al., 2019).

One branch of the literature is related to the impact of the target-based energy saving regulation. Those studies focus on exploring the effectiveness of regulations on individual firm during the 11 FYP period in China. Some existing studies verify the effectiveness of those regulations in micro-firm level. For instance, in iron and steel industry the T1000P can improve firm total factor productivity, and improve carbon emission performance (Filippini et al., 2020; Shao et al., 2023). The T1000P can improve firm energy intensity(Du et al., 2022). Shi et al.(2023) found that the T10000P in 12FYP period lead to energy saving and enhance through enhancing energy intensity and dynamically adjusting production scale. However, some scholars point out detrimental effect that cause by not well-designed regulation including over-ambitious reduction targets, and statistical inaccuracy(Zhao and Wu, 2016). During 11FYP period target-based energy constraint policy inhibit firm energy efficiency and firm green innovation efficiency, sub-sector total factor energy efficiency(Shao et al., 2019; Shi et al., 2022; Tang et al., 2020). In chemical industry the T1000P hamper firm total factor productivity(Ai et al., 2021). Furthermore, firms would carry out some adjustments to achieve the energy saving target or avoid burden of the regulation. In respond to T1000P regulated firms cut output and shift production to unregulated firms in the same conglomerate instead of improving energy efficiency(Chen et al., 2021). The T1000P affect optional choices of firms making their profitability decrease, and significant slowdown in the production growth of targeted firms cause concerns about carbon leakage due to increased production by less efficient producers(Xiao et al., 2023). Manipulation data to exaggerate or falsify performance during the T1000P period is detected(Karplus et al., 2020). 11 FYP environmental regulation have lay burden on firms, causing more taxes avoidance, and raise tax burden on low-emission firms(Geng et al., 2021).

3.Methodology and Data

3.1Data Sources

Individual enterprise characteristics derive from Chinese Industrial Enterprises Database(CIED) maintained by the National Bureau of Statistics of China (NBSC). We divides firms by province and then match on the basis of Brandt et al.(2012) to make the data more accurate. Energy consumption and pollution emissions obtained from Chinese Environmental Statistics Database(CESD), notable as the most comprehensive micro-level environmental data in China. Precise and fuzzy methods are simultaneously adopted to merge the CIED and CESD to build a large firm-level database from 2002-2010. Treatment firms participating in the T1000P originated from the NDRC, annual reports of government's assessment that exclude the firms that mandatory closure, bankruptcies, mergers, or other major changes in production and energy use. We manual find the T1000P participants in the firm database. The study uses the firms whose 2-digit industry code is similar to treatment firms.

To improve data quality. This paper uses the GDP conversion index as an alternative measure of inflation to replace the price factor in the nominal variables of enterprises samples. Furthermore, the study deletes following match data according to the accounting principle: (1) samples whose sales revenue is lower than the export delivery value; (2) samples of fixed assets or current assets larger than total assets; (3) samples with zero gross output value; (4) samples with gross output value or fixed assets below zero; (5) labors less than 5. These treatments can avoid the accounting statistical error, to ensure the good nature of the selected samples.

3.2Measure of energy efficiency

DEA is well established methodology to evaluate relative efficiencies(Zhou et al., 2008). Though various efficiency can be different, they all develop from technical efficiency, which refers to the ability to increase output given the same or lesser input units(Zhu and Lin, 2021). Technical efficiency indicates the relative distance from the decision making unit (DMU) to the production frontier. The closer the DMU is to the frontier, the higher the efficiency is.

Following Zhou et al.(2012) and Zhang et al.(2013), we employe the meta-frontier non-radial directional distance function to model energy efficiency as follow:

$$\overrightarrow{D^d}(x, y, b; g) = sup\{\mathbf{W}^T \boldsymbol{\beta}: (x, y, b) + g \times diag(\boldsymbol{\beta})\} \tag{1}$$

Where $\mathbf{W} = (W_m^x, W_s^y, W_j^b)^T$ denotes a normalized wright vector relevant to numbers of inputs and outputs, $g = (-g_x, g_y, -g_b)$ is an explicit directional vector, and $\boldsymbol{\beta} = (\beta_m^x, \beta_s^y, \beta_j^b)^T \geq 0$ denotes the vector of scaling factors. We adopt Python calculate the value of $\overrightarrow{D^d}(x, y, b; g)$ by solving the following model:

$$\overrightarrow{D^d}(x,y,b;g) = max W_m^x \beta_m^x + W_s^y \beta_s^y + W_j^b \beta_j^b$$
$$s.t. \sum_{n=1}^{N} z_n x_{mn} \leq x_m - \beta_m^x g_{xm}, m = 1, \dots, M,$$
$$\sum_{n=1}^{N} z_n y_{sn} \geq y_s + \beta_s^y g_{ys}, s = 1, \dots, S, \tag{2}$$
$$\sum_{n=1}^{N} z_n b_{jn} = b_j - \beta_j^b g_{bj}, j = 1, \dots, J,$$
$$z_n \geq 0, n = 1,2, \dots N,$$
$$\beta_m^x, \beta_s^y, \beta_j^b \geq 0$$

If $\vec{D}(x,y,b;g) = 0$, then the firm to be evaluated is located on the fronter of best practices in the direction of g. The input vector x contains capital(K), labor(L), and energy consumption(E), the desirable output y refers to total output, the undesirable output b refer to SO2 emission(Su). we set the weight vector as $(1/9, 1/9, 1/9, 1/3, 1/3)$. And the directional vectors as $g = (-K, -L, -E, V, -S\text{u})$. β_E^* are the optimal solutions corresponding to the input and the output in model(2). Energy potential reduction index was denoted as:

$$EPRI = \beta_E^* E \tag{3}$$

Following Zhou(2012) and Zhang et al.(2013) we define a total factor energy performance index($TEPI$) as:

$$TEPI = \frac{V/E}{(V + \beta_V^* V)/(E - \beta_E^* E)} = \frac{1 - \beta_E^*}{1 + \beta_V^*} \tag{4}$$

Clearly, $TEPI$ is between 0 and 1, and the higher the $TEPI$, the better the energy performance is. If $TEPI =$ 1, the sample shows the best energy performance on the technology frontier.

The input and output factors as follow: Capital(K): fixed asset. Labor(L): number of employee, Energy consumption(E): total energy consumption is equal to the total amount obtained by converting coal, fuel oil and gas into standard coal according to the standard coal factor and then adding them up.4 SO2 emission(Su). This study use sample firms in the targeted energy-intensive industries from 2002-2010. Description statistics of variables are shown in Table 1.

Table 1 Descriptive statistics.

		Variable	Min	Max	Std.Dev	Mean	Obs
Input		*asset*	0.79	142775568	1588064	227507.40	266254
		labor	1	185655	2197.29	554.50	266254
		energy	0.71	618877504	2335611	55292.46	266254
Output	desire	*y*	0.79	174598192	1673163	251704.20	266254
	undesire	*emission*	1.00	141266500	2336570	276580.70	266254

[4] Using the standard coal coefficients, with 0.7143, 0.9, 1.4286, 1.4571 and 1.33 for raw material coal, fuel coal, heavy oil, diesel and natural gas, respectively, converts various energy resources into a unified stranded.

Table 2 energy efficiency by industry from 2002 to 2010.[5]

industry	2002	2003	2004	2005	2006	2007	2008	2009	2010
non-ferrous metal	0.0172	0.0188	0.0265	0.0260	0.0340	0.0385	-	0.0442	0.0604
Iron&steel	0.0121	0.0161	0.0187	0.0207	0.0218	0.0265	0.0340	0.0337	0.0532
textile	0.0143	0.0156	0.0148	0.0193	0.0211	0.0247	0.0236	0.0253	0.0402
chemical	0.0124	0.0139	0.0149	0.0171	0.0191	0.0218	0.0242	0.0268	0.0363
Petroleum& petrochemicals	0.0110	0.0117	0.0148	0.0159	0.0169	0.0150	0.0185	0.0239	0.0312
coal	0.0050	0.0044	0.0070	0.0113	0.0097	0.0150	0.0184	0.0183	0.0443
paper	0.0093	0.0100	0.0107	0.0113	0.0126	0.0144	0.0156	0.0182	0.0250
Building materials	0.0057	0.0063	0.0068	0.0076	0.0088	0.0102	0.0118	0.0144	0.0172
Power& heat	0.0030	0.0032	0.0032	0.0042	0.0027	0.0036	0.0039	0.0050	0.0067

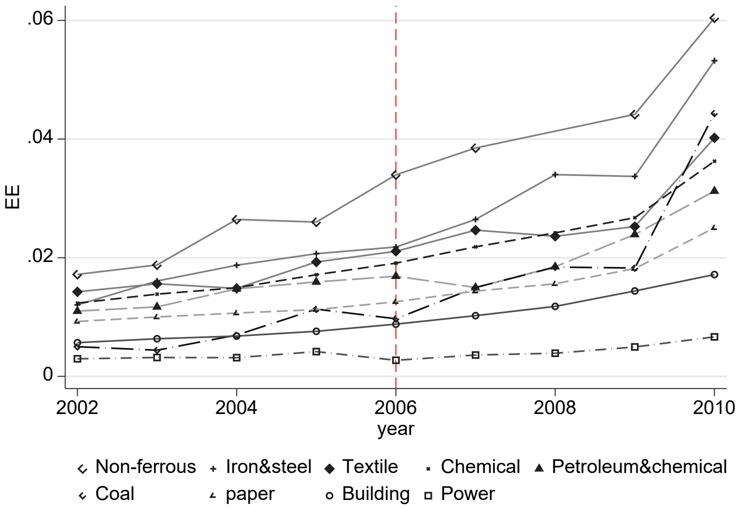

Fig.1. Trend of average energy efficiency in subsector from 2002-2010.

Table 2 shows the average energy efficiency of firms in sub-sectors, and power industry has the lowest energy efficiency. Energy efficiency is highly aligned with industry characteristics. Energy efficiency show gradually upward trend from 2002-2010. Fig.1 shows the distribution of energy efficiency difference within sectors over the study period. The kernel density plot of the energy efficiency difference between the 90th quartile firm and the 10th quartile firm, indicating this intra-industry dispersion measure

According to Fig.2, Many industries have high 90-10th differences, and this distribution of dispersions has a long left tail and skews to the right which is understand by the heterogenous of energy efficiency within sectors is large. The mean of the distribution in 2010(dark solid line) lies below the mean of all dispersion of other year, demonstrating that dispersion in 2010 for average industry heterogeneity is smaller than dispersion in other years. It means the intra-industry difference is gradually shrinking over time. This is particularly evident between 2008 and 2010. The gradual narrowing of the intra-industry energy efficiency difference indicates that the polarization gap between firms within sectors is narrowing, and the intra-industry energy efficiency has a tendency to converge.

[5] Chinese Industrial Enterprises Database(CIED) doesn't contain non-ferrous metal firms in 2008.

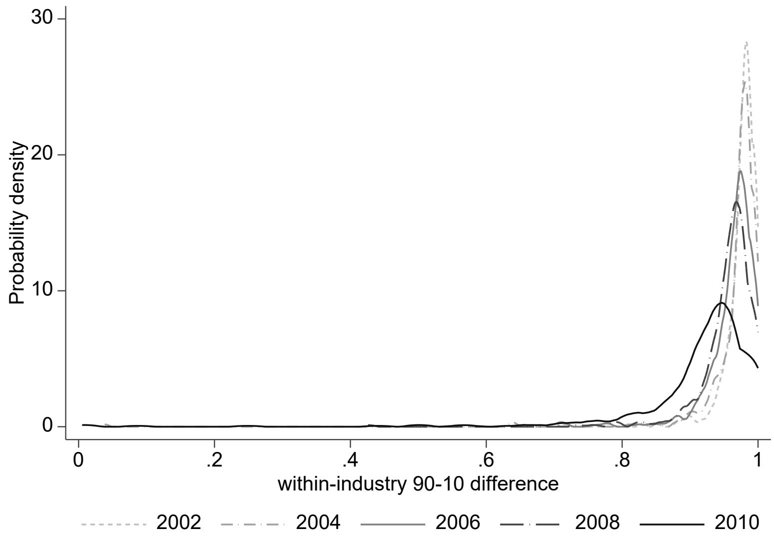

Fig.2. Distribution of within-industry 90-10th energy efficiency difference over the study period.

Fig.3 indicates that with significant regional differences, China shows a fluctuating upward trend from 2002 to 2010. It shows that firms in the east region have the best average energy efficiency for the period 2002–2010, followed by the central area. In addition, the gap between central regions and western regions in energy efficiency is widened since 2005. The growth rate of energy efficiency in western region was significantly lay far behind that in the central region. There exists a regional unbalance in terms of the energy efficiency, which is related to heterogeneity of regional resource endowments and infrastructure. The western region, while very rich in natural resources, lags behind the central and eastern region in economic development because of its poor infrastructure. Based on the heterogeneity of regional resources and infrastructure, policymakers should complement one-size-fit-all policies with locally tailored policies to promote energy efficiency and make them more effective.

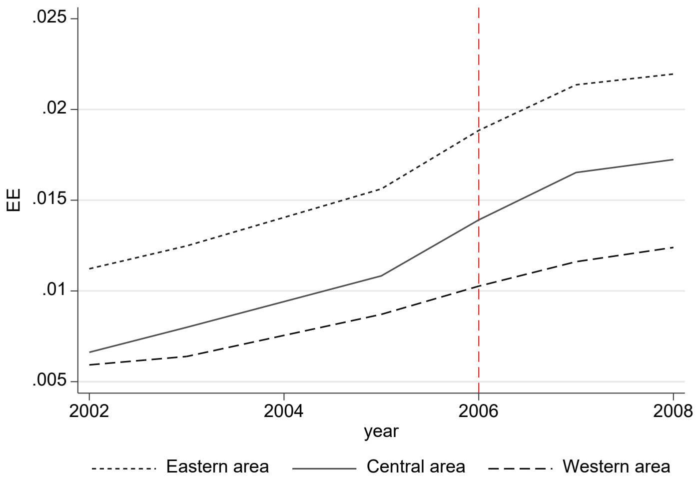

Fig.3. Trend in energy efficiency in three major regions of China from 2002 to 2010.

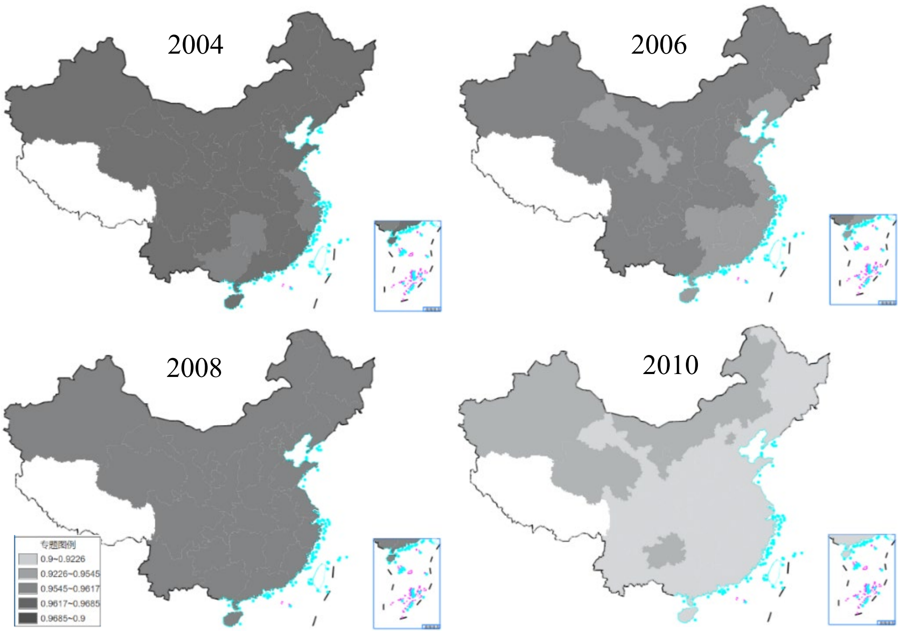

Fig.4. Intra-industry 90-10th energy efficiency difference by province over the study period.

Fig.4 shows the provincial mean of the difference of 90th to 10th percentiles in energy efficiency within sectors, showing the intra-industry energy efficiency heterogeneous within province. Overall, the heterogeneity in energy efficiency within sectors in the eastern areas are relatively small, followed by the central and western areas. In 2004-2010, the intra-industry energy efficiency heterogeneity in the western areas narrowed more slowly, probably due to the fact that during the 11FYP period, some firms moved westward, and the relocation of high-energy-efficiency firms widened the gap of energy saving technology.

In this study, we estimate the β convergence of energy efficiency. There are two types ofβconvergence: absolute and conditional. The absolute β convergence related to converging to a common to a common stable state and model is stated as:

$$g_{i,t+1} = \alpha + \beta lneff_{i,t} + \varepsilon_{i,t} \tag{5}$$

Where $g_{i,t+1}$ denotes the energy efficiency growth of firm i form period $t+1$ to the base year, represented by $\frac{lneff_{i,t+1} - lneff_{i,0}}{t+1}$, μ_i and η_t represent individual, time fixed effect, ε_{it} denotes the error term. If β is significantly negative, it indicates that there is absolute β convergence in energy efficiency, that is, energy efficiencies in different firms will eventually converge to the same steady state. At this time, firms with low energy efficiency can achieve the similar efficiency level as those firms with high energy efficiency by achieving rapid growth.

Table 3 absolute β convergence of energy efficiency

	overall	eastern	central	western
β	-0.806***	-0.826***	-0.833***	-0.727***
	(-266.42)	(-204.33)	(-147.18)	(-97.57)
α	-3.641***	-3.597***	-3.919***	-3.421***
	(-258.37)	(-198.63)	(-144.21)	(-92.28)
N	179630	96906	50808	31916
R^2	0.358	0.378	0.378	0.293

The conditional convergence allows various subsets of firms to converge to specific levels, depending on firm characteristic. The conditional convergence is modeled by controlling firm individual specific and time effects:

$$g_{i,t+1} = \alpha + \beta \mathrm{lneff}_{i,t} + \gamma X_i + \mu_i + \eta_t + \varepsilon_{i,t} \tag{6}$$

Where $g_{i,t+1}$ denotes the energy efficiency growth of firm i form period $t+1$ to the base year, represented by $\frac{lneff_{i,t+1}-lneff_{i,0}}{t+1}$, μ_i and η_t represent individual, time fixed effect, ε_{it} denotes the error term. X_i denotes the conditional variables. We control for firm size(Lny).

Table 4 conditional β convergence of energy efficiency.

	overall	eastern	central	western
β	-0.912***	-0.944***	-0.909***	-0.853***
	(-375.43)	(-296.65)	(-213.28)	(-128.19)
lny	0.690***	0.699***	0.667***	0.723***
	(274.36)	(213.40)	(167.00)	(85.56)
α	-11.69***	-11.87***	-11.53***	-11.77***
	(-372.37)	(-287.87)	(-231.01)	(-114.50)
N	179630	96906	50808	31916
R^2	0.597	0.626	0.651	0.464

The results of the absolute β convergence and conditional β convergence as presented in Table 3 and Table4. The β convergence are all significant.

3.3Estimation Strategy

Since the policy was announced in 2006 and selected firms based on their retrospective 2004 energy consumption, it was not possible to manipulate the list of program participants. The choice of firms of the T1000P was not random but related to energy consumption. There is heterogeneity, which leads to the different deviation of the DID method. To reduce the influence of deviations and confounding variables, and make a more reasonable and reliable comparison between the treatment groups and control groups, this study employs Propensity Score Matching-Difference in Difference(PSM-DID) method. We adopt logit model to estimate propensity score, then use one-to-one exact and nearest neighbor covariate matching method. Since technology heterogenous exists in different industry. To construct comparable control group, the treatment firm select the nearest firm under the same 2-digit industry code as control firm and their propensity score difference must be less than 0.05. Because the matched firms from the treatment and control group have a similar ex-ante likelihood of being in the T1000P, we can attribute the different in energy efficiency between treatment and control firms to the implement of the T1000P.

To estimate the effects of the external shocks on the impact of firm energy efficiency, the baseline regression model is set as follow:

$$eff_{it} = \alpha + \beta Post_t \times Treat_i + \gamma X_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{7}$$

In Eq(7), i and t denote firm and year respectively. eff_{it} represents the energy efficiency of firm i in year t. $Treat_i$ is set to 1 for the treatment firms eligible for the T1000P and 0 for control groups, $Post_t$ equals 1 if year for years since 2006 and 0 for other years, X_{it} denote a serious of firm-level control variables, μ_i and η_t represent industry, time fixed effect. ε_{it} is error term.

We introduce a set of variables at the firm level to control for the impacts mentioned above. The firm-level covariates include (1) Firm size(Lny), measured by the total outputs value of the firm. (2) Firm age(Age), expressed by the current year minus the established year of the firm. (3) Ownership type(Soe), an indicator of whether the firm is state-owned. (4) Profitability (profit), reflecting the profitability of the enterprise: total profit/total fixed assets. (5) Innovation(Lnnew_density), new product density measured by the ratio of new products to the total output value. It indicates firms' innovative capacity.

4.Empirical Results

4.1Baseline results

4.1.1Baseline regression

Baseline results are displayed in Table 5 Column (1) controls for industry fixed effects, firm-level fixed effects and year fixed effects. Column (2) adds city fixed effects to this, Column (3) (4) show the results remains unchanged after including control variables. Column (1)-(4) indicates that the T1000P is negatively correlated with firm energy efficiency, with the coefficient being statistically significant. The point estimate of β shows that the implement of the T1000P leads to the decrease of the treatment firms' energy efficiency by 38.4% on average(firms' average energy efficiency is 0.0130), which is significant at the 1% significance level.

The baseline results indicate that mandatory energy conservation constraints, the T1000P, inhibits firm energy efficiency. Under the energy conservation constraints and local government supervision, such as power cuts, temporary shutdown, and expert inspections, the enterprise would carry out some adjustments to achieve the energy saving targets, negatively affecting firms' energy efficiency. Overall, the crowding-out effect of the compulsory regulation larger than the innovation effect.

Table 5 Baseline Results.

	(1)	(2)	(3)	(4)
	eff	*eff*	*eff*	*eff*
$Post \times Treat$	-0.005***	-0.005***	-0.005***	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
lny			0.006***	0.006***
			(0.00)	(0.00)
age				0.001***
				(0.00)
City FE		Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	4280	4280	4280	4264
R^2	0.048	0.048	0.070	0.070

Notes: t-statistics are provided in brackets. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. FE is fixed effects. Here Y means "Yes"and N means "No", similarly hereinafter.

4.1.2PSM balance check

Matching variables need to fulfil the criteria that it affects both the explained variable and the sample participation decision. Thus, Firm size(Lny), Energy Consumption in 2004(lnE2004), Profitability (profit), Ownership type(Soe) are selected as the covariates. The matching procedure effectively addresses sample selection bias and heterogeneity, ensuring the research results are more robust and reliable. A balance check is conducted on the matched data to guarantee the effectiveness of policy evaluation. As depicted in Table 6, providing details of matching variables before and after the PSM. We can see that the estimated bias of all variables after matching declines significantly to within 20%. Moreover, the t-test results for all variables are non-significant after matching, indicating that there is no significant difference between the treatment and control groups.

Table 6 Balance test of variables before and after PSM.

Variable	Unmatched/ matched	Mean		bias(%)	Bias reduce(%)	t-test
		Treated	Control			
lny	UN	14.061	10.758	156.8	85.5	3.041***
	M	13.389	14.069	22.7		-0.645*
lnE_{2004}	UN	12.147	7.781	237.6	94.7	3.608***
	M	12.024	10.688	12.7		1.545
profit	UN	-0.011	0.244	-1.7	59.5	-0.097
	M	-0.046	-.150	0.7		0.0405
soe	UN	0.415	0.118	71.2	87.1	0.282***
	M	0.344	0.437	-9.2		-0.083

4.1.3Parallel trend test

The vital assumption for the validity of the DID method is the parallel trend assumption, which requires a consistent trend in energy efficiency during the pre-shock period for both the treatment and control groups. To verify the parallel trend assumption is satisfied, we examine the trends of the T1000P in the first 3 years and the sequent 5 years, and designate the year before the policy implementation as the basic period. Fig.5 (a)(b) dependent variables are energy efficiency, energy intensity(lnintensity), respectively. As show in Fig.5 the coefficient of policy is not significant, indicating prior to policy there is no significant difference in energy efficiency between the treatment and control groups. Obviously, the parallel trend assumption for PSM-DID estimation is confirmed.

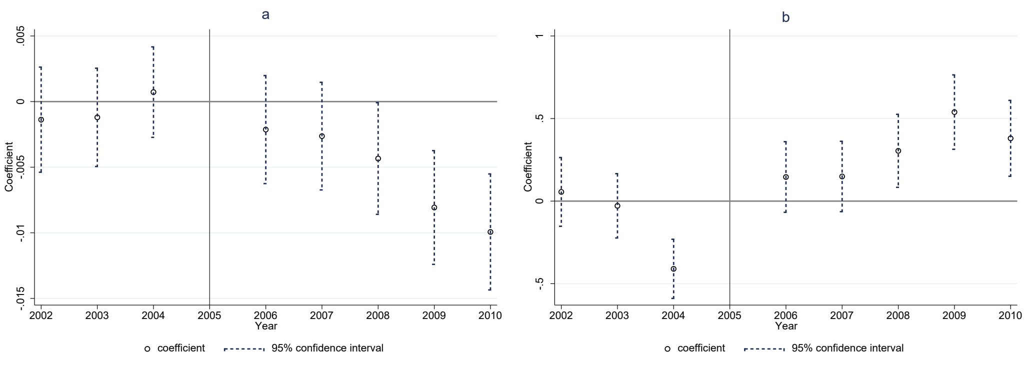

Fig.5. The dynamic impact of T1000P on energy efficiency

4.2Robustness Checks

The dependent variable of Columns (1)–(4) is energy intensity(logarithm of the ratio of energy consumption to total industrial output) in Table 7, and it shows the coefficient of the policy is significantly positive. Affected by the T1000P the increase of energy intensity-reduction of energy efficiency- aligns with the baseline results. The compulsory energy conservation regulation hinders the improvement of firm energy efficiency. Therefore, the result still hold.

Table 7 Regression results for firms' energy intensity.

	(1)	(2)	(3)	(4)
	lnintensity	*lnintensity*	*lnintensity*	*lnintensity*
$Post \times Treat$	0.459***	0.451***	0.399***	0.399***
	(0.07)	(0.07)	(0.07)	(0.07)
lny			-0.667***	-0.667***
			(0.04)	(0.04)
age				0.002
				(0.01)
City FE		Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	4280	4280	4280	4264
R^2	0.038	0.040	0.139	0.139

4.2.1Change Matching method

In ensure treatment and control groups have characteristics that are as similar as possible, to reduce the bias caused by a non-random sample selection, we change the matching method. We further adopt one-to-four exact and nearest neighbor covariate matching method, radius matching, kernel matching method as a robustness test. and the regression analysis is performed again using the data obtained after matching. As reported in Table 8, the regression coefficient of Eq(7) is negative, which is significant at the 1% level. The results of changing matching method are consistent with the result shown previously, which verifies that any bias caused by sample selection does not affect our conclusion.

Table 8 Regression results for changing matching method.

	(1)	(2)	(3)	(4)	(5)	(6)
	1:4Nearest *eff*	1:4 Nearest *eff*	Radius *eff*	Radius *eff*	kernel *eff*	kernel *eff*
$Post \times Treat$	-0.004***	-0.004***	-0.005***	-0.005***	-0.003***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lny	0.010***	0.010***	0.008***	0.008***	0.009***	0.009***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
age		0.001***		0.001***		0.001***
		(0.00)		(0.00)		(0.00)
City FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
N	36563	36469	17975	17932	25463	25397
R^2	0.112	0.111	0.101	0.101	0.112	0.112

4.2.2Exclude Other Policies

Along with the goals to save energy in the energy-intensive sectors via the t T1000P, the national government also implemented a program to eliminate outdated production capacity during the 11YFP. The program defined production technologies that would be limited or eliminated in all sectors(NDRC, 2005). These firms were required to shut down or retire or update part of their production capacity.

The effects of the T1000P constraint on energy efficiency might be interfered with by other concurrent policies, thereby affecting the robust of our results. To address this concern, we attempt to eliminate the impact of other environmental regulation or polices. During the 11YFP Chinese government also implemented a policy to phase out obsoleted industrial production in specific industry(NDRC, 2005). The program aimed to make substantial progress in restricting industrial production with high-energy intensity and backward technology, including energy quote, power outages, and the small plant closure program. Those restrictions were limited in specific energy-intensive sectors. Thus, we eliminate the firm samples in industry that overlap the policy. Based on sub-samples, we re-estimate the effect of the T1000P using baseline regression. Table 9 presents the estimated result after excluding other policies, finding results remain strongly robust.

Table 9 Regression results for excluding other policies.

	(1)	(2)	(3)	(4)
	eff	*eff*	*lnintensity*	*lnintensity*
$Post \times Treat$	-0.001*	-0.003***	0.434***	0.434***
	(0.00)	(0.00)	(0.13)	(0.13)
lny	0.002***	0.001**	-0.771***	-0.771***
	(0.00)	(0.00)	(0.06)	(0.06)
age		0.000***		0.017
		(0.00)		(0.02)
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	894	890	894	890
R^2	0.024	0.036	0.254	0.254

4.2.3Placebo Test

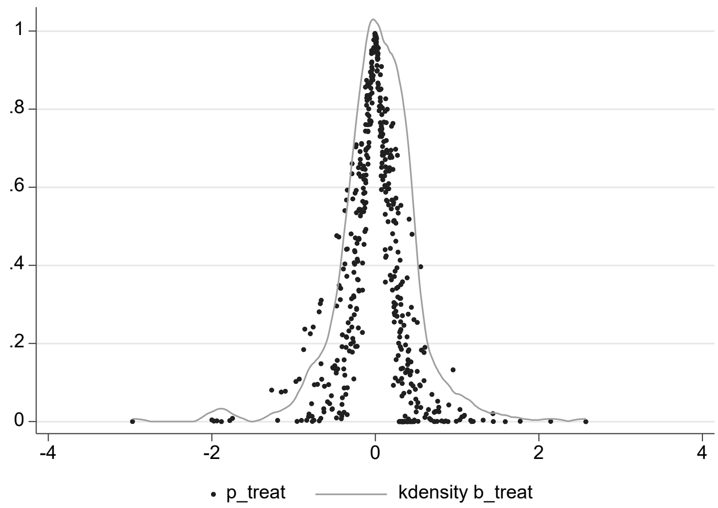

Fig.6. Placebo test-coefficient distribution.

To exclude unobservable systematic factors that may interfere with the results, this study constructs a counterfactual framework for the placebo test. We run simulations that artificial allocate our sample firm to treatment group in 2004. In each simulation, we apply to bootstrap to randomly assign the treatment dummy to the whole sample and then conduct the baseline PSM-DID regression based on this pseudo-sample. Repeat the simulation process 500 times. The coefficients from the placebo test are reported in Fig.6. The estimated results are reported in approximately normally distributed and mostly clustered around 0. Meanwhile, most of the estimated p-values are above 0.100 (not significant at the 10% level), which means that the estimated results above are unlikely driven by chance. Thus, the result we obtain has not been affected by other policies or random factors, which meets the expectations of the placebo test. This indicates that confounding and ongoing policies would not affect the results, proving the robustness of the main findings.

4.3Heterogeneity Analysis

Due to different firm characteristic, how firms respond to the T1000P really various a lot. We further examine the heterogeneous effects of the T1000P between state-own and nonstate-own firms. By classifying firms by ownership and introducing them into baseline regression, the results was displayed in Table 9. Table 9 reveals the coefficients of the T1000P are significant negative in different ownership sub-samples, and the negative impact of the T1000P on energy efficiency is more pronounced in state-own firms. Column (1) indicates that the T1000P has significant negative impact on state-own firms' energy efficiency, decreasing of the sate-own firms' energy efficiency by 49.8% on average(state-own firms' average energy efficiency is 0.01203). Column (2) shows that the program negatively affects nonstate-own firms' energy efficiency and leads to the decrease of the nonstate-own firms' energy efficiency by 21.6% on average(nonstate-own firms' average energy efficiency is 0.02320). The findings are not counterintuitive. Government intervention in the state-own firms is strong, and by adopting more stringent supervision means and target-based performance promotion system, the state-own firms burden more pressure to achieve the targets, thereby restraining the firms' flexibility and negatively affecting firms' energy efficiency. When the regulator imposed a stringent energy constraint on the firm, the added pressure on a state-own firms could make them more susceptible to substituting output to other compliant facilities, leading crowding-out effect on innovation investment further lower energy efficiency. The firm ownership is a crucial factor affecting the effectiveness of the energy conservation regulation, which provides valuable insights for the future policy development.

Table 9 Regression results for heterogeneity analysis.

	(1)	(2)	(3)	(4)
	State-own	nonState-own	ResourceCity	nonResourceCity
	eff	*eff*	*eff*	*eff*
$Post \times Treat$	-0.006*	-0.005***	-0.002	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
lny	0.004***	0.006***	0.007***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	1350	2930	1641	2639
R^2	0.032	0.108	0.043	0.049

Based on National Sustainable Development Plan for Resource Cities (2013-2020) issued by the State Council, we identify resource-development cities. Table 9 Column (3)(4) present the T1000P differently affects firms from cities with different resource endowment. The decline in energy efficiency for firms in non-resource-developing city is significant at the 1% level, while for firms in resource-development city the reduction effect is not significant. Naturally, energy-intensive firms are closely dependent on energy resources, firms in resource-development cities could optimize the energy structure leveraging the rich resource endowment when faced with energy constraints. The firms from non-resource-developing cities, on the contrary, are not able to adjust energy structure in a short run. Thus, the adverse effects more pronounced on firms from non-resource-developing cities. Besides, Factors cannot flow freely between regions, which may exacerbate resource mismatch suppressing energy inefficiency improvement.

4.4Mechanism Tests

4.4.1Factor Reallocation

The mandatory environmental regulation may cause resource reallocation within firms, which causes resource misallocation and has negative effect on the firm energy efficiency. The firm may carry out some adjustment on production、 asset and labor to achieve the energy saving target.

The T1000P may have opposite effect on the firm production. In the absence of improvement of energy efficiency, firms have incentive to realize the targets by expanding the size of production. On the other hand, phasing out old inefficiency parts of production, investment in new equipment may crowd out production size, and constraints from local government-power cutting and production restriction-may discourage product activity. The opposite effect on production size can happen simultaneously. The mandatory environmental regulation most likely to hinder the production of targeted firms.

There are two asset adjustments in opposing directions when firms are subject to the Top program. Investment in new equations may be in relation to the increase of fixed asset. However, phasing out old inefficiency assembly lines lead to decline of fixed asset. Compliance cost may crowd out investment of fixed asset, reducing the fixed asset.

The T1000P may cause firms to adjust their labors. If the firms replace the inefficiency assembly lines with new technology assembly lines, it may be labor saving. Because new capital is usually labor saving, the employment level of firms with replacement investment may decline, stay unchanged or at least not increase as fast as the increase of their fixed capital assets, depending on the extent to which new production capital changes the level of production capacity.

Table 10 reports the estimated results using the form of Eq(7). The dependent variable of column (1) is logarithm of industrial output, which show the T1000P have negative effect on firms' output. This is aligned with existing studies by Chen et al.(2021) and Xiao et al.(2023). Column (2) indicates that the Top program decrease the fixed asset significantly. According to column (3), the labor saving is not significant. Thus, it shed light on that the participants reallocate input factors.

Table 10 Regression results for factor reallocation.

	(1)	(2)	(3)	(4)	(5)
	lny	*lnasset*	*labor/asset*	BPC	Lnnew_density
$Post \times Treat$	-0.074**	-0.088**	0.006	-0.099	-0.687***
	(0.03)	(0.04)	(0.07)	(0.87)	(0.26)
age	0.121***		0.006		-0.136***
	(0.01)		(0.01)		(0.04)
$labor$	0.000***	0.000***			
	(0.00)	(0.00)			
lny			0.068*	-1.935***	-0.351*
			(0.04)	(0.59)	(0.20)
City FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
N	4264	4280	4264	3384	447
R^2	0.344	0.115	0.003	0.257	0.301

4.4.2Innovation Effect

Technology innovation has been proven to be an important contributor to firm energy efficiency. The result is aligned with the crowding-out effect of environmental regulation on energy efficiency. The innovation effect of the T1000P doesn't offset the compliance effect, which has hampered the improvement of energy efficiency.

Following Oh and Lee(2010) we define three technology set to calculate the component distance functions: a contemporaneous benchmark technology set, an intertemporal benchmark technology set, and a global benchmark technology set. It can be decomposed as:

$$MML_t^{t+1} = \frac{1+\vec{D}^G(x^t, y^t, b^t)}{1+\vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})}$$

$$= \frac{1+\vec{D}^t(x^t, y^t, b^t)}{1+\vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}$$

$$\times \frac{(1+\vec{D}^I(x^t,y^t,b^t))\ /\ (1+\vec{D}^t(x^t,y^t,b^t))}{(1+\vec{D}^I(x^{t+1},y^{t+1},b^{t+1}))\ /\ (1+\vec{D}^{t+1}(x^{t+1},y^{t+1},b^{t+1}))}$$

$$\times \frac{(1+\vec{D}^G(x^t,y^t,b^t)) \;/\; (1+\vec{D}^I(x^t,y^t,b^t))}{(1+\vec{D}^G(x^{t+1},y^{t+1},b^{t+1})) \;/\; (1+\vec{D}^I(x^{t+1},y^{t+1},b^{t+1}))}$$

$$= \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t}$$

$$= EC \times BPC \times TGC \tag{8}$$

The global benchmark technology of all groups is define as $\vec{D}^G$, the intertemporal benchmark technology of every industry is defined as $\vec{D}^I$, a contemporaneous benchmark technology of every group in one period is defines as $\vec{D}^t$. EC is the efficiency change measure. BPC is the change in best practice gap, it provides a measure of technical change within a group. BPC > 1(< 1) is equivalent to the technical progress (regress). TGR measures the technology gap between the technology level for the j th group relative to the potential technology level that is defined by the global technology set. TGR is change in technology leadership. We adopt BPC as firm innovation. Table 10 column (4) indicates that the T1000P have negative effect on firms innovation, which is not significant. So the mandatory energy efficiency improvement regulation did not stimulate the capacity of innovation, which is aligned with our expectation.

Follow Li et al.(2021) and Shi et al.(2022) we apply new product intensity as an innovation measure to explore the innovation channel. Table 10 Column (5) shows that the T1000P hinders the firms' innovation capacity(we adopt firms' new products output isn't equal to 0). Since the innovation is curtail to the improvement of energy efficiency, it demonstrates the T1000P may sabotage firm innovation, further lowing firm energy efficiency.

5.Concluaions and Policy Implications

Under the background of rising energy demand, frequent energy crisis and widespread concerns about climate change, improving energy efficiency policy was adopt in many nations. In this paper, we investigate how policy aiming at improving energy efficiency affects firm energy efficiency. we use the T1000P in China as a quasi-natural experiment, employ a PSD-DID identification framework to empirical analysis the impact of the target based mandatory environmental regulation. The results provide strong evidence that the T1000P inhibits energy efficiency of participants. This finding is consistent with the view that the stringent command-and-control environmental regulation cause compliance cost. In addition, the energy efficiency of participants did not increase but decrease, which means the "innovation offsets" is not valid when they are subject to the T1000P.

Heterogeneity analyses show that the implement of the T1000P on energy efficiency varies by firm ownership and region with different resource endowment. The state-own firms burden more pressure to achieve the energy saving targets causing more energy inefficiency, which is closely related to stringent supervision from local authorities. Participants in region with poor resource endowment may gain more adverse impact from the T1000P, which prove from the side that market barriers hindering the flow of factors between regions exist. Besides, we find the T1000P would cause resource reallocation within firm and hinder the firm innovation, thereby inhibiting firm energy efficiency.

The above conclusions have important and realistic policy implications. Firstly, Improper and ambitious energy intensity reduction targets usually mean more stringent and irrational measures to achieve such targets. Thus, it is essential to set reasonable energy targets based on specific detail analysis of the firm characteristics and specific industry. Inappropriate regulation not only affect the dispersion in productivity across firms but are also likely to hinder the allocation of resources towards the most productive one, and regulations hurt in particular those firms that have the potential to excel in domestic and international market(Arnold et al., 2008).

Secondly, compared with the command-and-control environmental regulation, the market incentive regulation has less distortion to factor markets, allocating resources more efficient. The one-size-fit-all mandatory intervention such as power cutting and production restriction hamper the autonomy of firms, and flexibility of adjustment. It more favorable to realizing improvement of energy efficiency with the help of market forces and moderate government intervention. Incentive environmental regulation is more conductive to the formation of a virtuous circle of "innovative decision"-"technological upgrading"-"innovation compensation" (Xu and Xu, 2022).

Moreover, the decisive role of the market in resource allocation must be given full play. Specifically, it is crucial to break the administrative monopoly that hinders the flow of factors, reduce the direct allocation of factors by the government, and eliminate the transaction costs caused by information asymmetry and inter-regional trade barriers. Encouraging competition and collaboration between regions by dismantling market barriers is key.

CRediT authorship contribution statement

Yue Xu: Data curation, Methodology, Software, Writing – original draft. **Xiaolan Chen**: Conceptualization, Supervision~~, Writing – review & editing.~~

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

References

Ai, H., Hu, Y., Li, K., 2021. Impacts of environmental regulation on firm productivity: evidence from China's Top 1000 Energy-Consuming Enterprises Program. Applied Economics 53, 830–844. https://doi.org/10.1080/00036846.2020.1815642

Arnold, J.M., Nicoletti, G., Scarpetta, S., 2008. Regulation, Allocative Efficiency and Productivity in OECD Countries: Industry and Firm-Level Evidence (OECD Economics Department Working Papers No. 616), OECD Economics Department Working Papers. https://doi.org/10.1787/241447806226

Boyd, G.A., McClelland, J.D., 1999. The Impact of Environmental Constraints on Productivity Improvement in Integrated Paper Plants. Journal of Environmental Economics and Management 38, 121–142. https://doi.org/10.1006/jeem.1999.1082

Brandt, L., Van Biesebroeck, J., Zhang, Y., 2012. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. Journal of Development Economics 97, 339–351. https://doi.org/10.1016/j.jdeveco.2011.02.002

Bu, C., Zhang, K., Shi, D., Wang, S., 2022. Does environmental information disclosure improve energy efficiency? Energy Policy 164, 112919. https://doi.org/10.1016/j.enpol.2022.112919

Chambers, R.G., Chung, Y., Färe, R., 1998. Profit, Directional Distance Functions, and Nerlovian Efficiency.

Journal of Optimization Theory and Applications 98, 351–364. https://doi.org/10.1023/A:1022637501082
Chambers, R.G., Chung, Y., Färe, R., 1996. Benefit and Distance Functions. Journal of Economic Theory 70, 407–419. https://doi.org/10.1006/jeth.1996.0096
Chen, D., Chen, S., Jin, H., Lu, Y., 2020. The impact of energy regulation on energy intensity and energy structure: Firm-level evidence from China. China Economic Review 59, 101351. https://doi.org/10.1016/j.chieco.2019.101351
Chen, Q., Chen, Z., Liu, Z., Serrato, J.C.S., Xu, D.Y., 2021. Regulating Conglomerates: Evidence from an Energy Conservation Program in China.
Cheng, Z., Liu, J., Li, L., Gu, X., 2020. Research on meta-frontier total-factor energy efficiency and its spatial convergence in Chinese provinces. Energy Economics 86, 104702. https://doi.org/10.1016/j.eneco.2020.104702
Chiu, C.-R., Liou, J.-L., Wu, P.-I., Fang, C.-L., 2012. Decomposition of the environmental inefficiency of the meta-frontier with undesirable output. Energy Economics 34, 1392–1399. https://doi.org/10.1016/j.eneco.2012.06.003
Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO2 emissions in China: A slacks-based efficiency measure. Applied Energy 98, 198–208. https://doi.org/10.1016/j.apenergy.2012.03.024
Curtis, E.M., Lee, J.M., 2019. When do environmental regulations backfire? Onsite industrial electricity generation, energy efficiency and policy instruments. Journal of Environmental Economics and Management 96, 174–194. https://doi.org/10.1016/j.jeem.2019.04.004
Du, W., Li, M., Wang, Z., 2022. Open the black box of energy conservation: Carbon reduction policies and energy efficiency of microcosmic firms in China. Energy Strategy Reviews 44, 100989. https://doi.org/10.1016/j.esr.2022.100989
Färe, R., Grosskopf, S., 2010. Directional distance functions and slacks-based measures of efficiency. European Journal of Operational Research 200, 320–322. https://doi.org/10.1016/j.ejor.2009.01.031
Filippini, M., Geissmann, T., Karplus, V.J., Zhang, D., 2020. The productivity impacts of energy efficiency programs in developing countries: Evidence from iron and steel firms in China. China Economic Review 59, 101364. https://doi.org/10.1016/j.chieco.2019.101364
Fukuyama, H., Weber, W.L., 2009. A directional slacks-based measure of technical inefficiency. Socio-Economic Planning Sciences 43, 274–287. https://doi.org/10.1016/j.seps.2008.12.001
Geng, Y., Liu, W., Li, K., Chen, H., 2021. Environmental regulation and corporate tax avoidance: A quasi-natural experiment based on the eleventh Five-Year Plan in China. Energy Economics 99, 105312. https://doi.org/10.1016/j.eneco.2021.105312
Gollop, F.M., Roberts, M.J., 1983. Environmental Regulations and Productivity Growth: The Case of Fossil-fueled Electric Power Generation. Journal of Political Economy 91, 654–674. https://doi.org/10.1086/261170
Gray, W.B., 1987. The Cost of Regulation: OSHA, EPA and the Productivity Slowdown. The American Economic Review 77, 998–1006.
Guo, Q., Dong, Y., Feng, B., Zhang, H., 2023. Can green finance development promote total-factor energy efficiency? Empirical evidence from China based on a spatial Durbin model. Energy Policy 177, 113523. https://doi.org/10.1016/j.enpol.2023.113523
Hu, J.-L., Wang, S.-C., 2006. Total-factor energy efficiency of regions in China. Energy Policy 34, 3206–3217. https://doi.org/10.1016/j.enpol.2005.06.015
ICCSD Tsinghua University, 2022. China's Long-Term Low-Carbon Development Strategies and Pathways: Comprehensive Report. Springer Singapore, Singapore. https://doi.org/10.1007/978-981-16-2524-4
IEA, 2022. Energy Efficiency 2022. https://www.iea.org/reports/energy-efficiency-2022

Karplus, V.J., Shen, X., Zhang, D., 2020. Herding Cats: Firm Non-Compliance in China's Industrial Energy Efficiency Program. EJ 41. https://doi.org/10.5547/01956574.41.4.vkar

Li, S., Liu, J., Shi, D., 2021. The impact of emissions trading system on corporate energy efficiency: Evidence from a quasi-natural experiment in China. Energy 233, 121129. https://doi.org/10.1016/j.energy.2021.121129

Lyu, C., Xie, Z., Li, Z., 2022. Market supervision, innovation offsets and energy efficiency: Evidence from environmental pollution liability insurance in China. Energy Policy 171, 113267. https://doi.org/10.1016/j.enpol.2022.113267

Mandal, S.K., 2010. Do undesirable output and environmental regulation matter in energy efficiency analysis? Evidence from Indian Cement Industry. Energy Policy 38, 6076–6083. https://doi.org/10.1016/j.enpol.2010.05.063

Oh, D. hyun, Lee, J. dong, 2010. A metafrontier approach for measuring Malmquist productivity index. Empirical economics 38, 47–64.

Patterson, M.G., 1996. What is energy efficiency? Energy Policy 24, 377–390. https://doi.org/10.1016/0301-4215(96)00017-1

Peng, C., Zhang, J., Xu, Z., 2022. Does Price Distortion Affect Energy Efficiency? Evidence from Dynamic Spatial Analytics of China. Energies 15, 9576. https://doi.org/10.3390/en15249576

Porter, M.E., Linde, C.V.D., 1995. Toward a New Conception of the Environment-Competitiveness Relationship. Journal of Economic Perspectives 9, 97–118. https://doi.org/10.1257/jep.9.4.97

Price, L., Wang, X., Yun, J., 2010. The challenge of reducing energy consumption of the Top-1000 largest industrial enterprises in China. Energy Policy 38, 6485–6498. https://doi.org/10.1016/j.enpol.2009.02.036

Qu, C., Shao, J., Shi, Z., 2020. Does financial agglomeration promote the increase of energy efficiency in China? Energy Policy 146, 111810. https://doi.org/10.1016/j.enpol.2020.111810

Shao, S., Xu, L., Yang, L., Yu, D., 2023. Effectiveness of production-oriented carbon reduction projects: evidence from the top 1000 energy-consuming enterprises program. Ann Oper Res. https://doi.org/10.1007/s10479-023-05442-y

Shao, S., Yang, Z., Yang, L., Ma, S., 2019. Can China's energy intensity constraint policy promote total factor energy efficiency? Evidence from the industrial sector. The Energy Journal 40.

Shi, D., Yang, Z., Ji, H., 2022. Energy target-based responsibility system and corporate energy efficiency: Evidence from the eleventh Five Year Plan in China. Energy Policy 169, 113214. https://doi.org/10.1016/j.enpol.2022.113214

Shi, G.-M., Bi, J., Wang, J.-N., 2010. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy 38, 6172–6179. https://doi.org/10.1016/j.enpol.2010.06.003

Shi, X., 2023. How do regulatory environmental policies perform? A case study of China's Top-10,000 enterprises energy-saving program. Renewable and Sustainable Energy Reviews.

Tanaka, K., 2011. Review of policies and measures for energy efficiency in industry sector. Energy Policy 39, 6532–6550. https://doi.org/10.1016/j.enpol.2011.07.058

Tang, K., Qiu, Y., Zhou, D., 2020. Does command-and-control regulation promote green innovation performance? Evidence from China's industrial enterprises. Science of The Total Environment 712, 136362. https://doi.org/10.1016/j.scitotenv.2019.136362

Wang, H., Chen, Z., Wu, X., Nie, X., 2019. Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the porter hypothesis? —Empirical analysis based on the PSM-DID method. Energy Policy 129, 930–938. https://doi.org/10.1016/j.enpol.2019.03.007

Wu, H., Hao, Y., Ren, S., 2020. How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. Energy Economics 91, 104880.

https://doi.org/10.1016/j.eneco.2020.104880
Xiao, Y., Yin, H., Moon, J.J., 2023. Coping with Externally Imposed Energy Constraints: Competitiveness and Operational Impact of China's Top-1000 Energy-Consuming Enterprises Program. EJ 44. https://doi.org/10.5547/01956574.44.2.yxia
Xu, B., Xu, R., 2022. Assessing the role of environmental regulations in improving energy efficiency and reducing CO2 emissions: Evidence from the logistics industry. Environmental Impact Assessment Review 96, 106831. https://doi.org/10.1016/j.eiar.2022.106831
Zhang, N., Choi, Y., 2014. A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. Renewable and Sustainable Energy Reviews 33, 50–59. https://doi.org/10.1016/j.rser.2014.01.064
Zhang, N., Kong, F., Choi, Y., Zhou, P., 2014. The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants. Energy Policy 70, 193–200. https://doi.org/10.1016/j.enpol.2014.03.031
Zhang, N., Zhao, Y., Wang, N., 2022. Is China's energy policy effective for power plants? Evidence from the 12th Five-Year Plan energy saving targets. Energy Economics 112, 106143. https://doi.org/10.1016/j.eneco.2022.106143
Zhang, N., Zhou, P., Choi, Y., 2013. Energy efficiency, CO2 emission performance and technology gaps in fossil fuel electricity generation in Korea: A meta-frontier non-radial directional distance functionanalysis. Energy Policy 56, 653–662. https://doi.org/10.1016/j.enpol.2013.01.033
Zhao, X., Li, H., Wu, L., Qi, Y., 2016. Enterprise-level amount of energy saved targets in China: weaknesses and a way forward. Journal of Cleaner Production 129, 75–87. https://doi.org/10.1016/j.jclepro.2016.04.116
Zhao, X., Wu, L., 2016. Energy saving calculation and target assessment of industrial enterprises, in: Annual review of low-carbon development in China(2015-2016). Social Sciences Academic Press(China), pp. 136–154.
Zhou, N., Levine, M.D., Price, L., 2010. Overview of current energy-efficiency policies in China. Energy Policy 38, 6439–6452. https://doi.org/10.1016/j.enpol.2009.08.015
Zhou, P., Ang, B.W., 2008. Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 36, 2911–2916. https://doi.org/10.1016/j.enpol.2008.03.041
Zhou, P., Ang, B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research 189, 1–18. https://doi.org/10.1016/j.ejor.2007.04.042
Zhou, P., Ang, B.W., Wang, H., 2012. Energy and CO2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research 221, 625–635. https://doi.org/10.1016/j.ejor.2012.04.022
Zhu, R., Lin, B., 2021. Energy and carbon performance improvement in China's mining Industry:Evidence from the 11th and 12th five-year plan. Energy Policy 154, 112312. https://doi.org/10.1016/j.enpol.2021.112312