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Electricity Supply Unreliability and Technical Efficiency: Evidence from Listed Chinese Manufacturing Companies

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Abstract: This study examines the extent to which electricity shortage influences technical efficiency using data of 805 listed manufacturing companies in China from 2009 to 2020 collected from the CSMAR database. To achieve the objectives of this paper, first, a stochastic frontier analysis (SFA) is used to estimate the technical efficiency (TE) score of manufacturing companies. Subsequently, the TE score is used to evaluate the electricity shortage index and other factors that are postulated to affect enterprise productivity. Two estimation methods have been adopted including ordinary least squares (OLS), which is less robust to endogeneity and instrumental variable (IV) estimation, which turns out to be more robust to endogeneity in the data. The empirical results show that, under OLS estimation, electricity shortage has a significantly negative impact on the technical efficiency of the listed manufacturing companies. However, when IV regression is implemented to address endogeneity issues in the data, electricity shortages tend to have a significantly positive impact on the technical efficiency, underscoring the importance of capturing endogeneity in the data. Extending the baseline results, this study also finds that, while the size of an enterprise may have no bearing, state-owned companies are more likely to be negatively affected by electricity shortages compared to privately owned companies. These results have significant implications for industrial policy design in China in particular, and developing countries in general. Most importantly, the results of this study underscore the importance of policies and measures to promote a shift in the ownership structure towards the private sector.

Keywords: electricity shortage; technical efficiency; stochastic frontier analysis; China

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1. Introduction

Economic development has long plagued human society. On 25–27 September 2015, at the 70th session of the United Nations General Assembly, 193 member states unanimously adopted the outcome document "Transforming our World—The 2030 Agenda for Sustainable Development", which proposed to eradicate all forms of global poverty by 2030. Goal 7 of the agenda was to ensure access to affordable, reliable, and sustainable modern energy for all. The availability of resources and the reliability of input factors are important for business productivity and for some resources, water and storage devices. However, unreliable electricity supply requires businesses to respond in other ways because of the high cost of electricity storage [1,2]. In retrospect, China has experienced four major power restrictions since 2000. The year of 2003 saw a rapid increase in electricity consumption by domestic heavy industries combined with persistent hot weather, with the country's electricity consumption increasing by 15.4% year-on-year in that year, which was the fastest growth since the reform and opening up. In addition, the overall dryness of water from major hydropower stations in 2003 exacerbated the imbalance between the electricity supply and demand, with a total of 22 provinces and cities experiencing power cuts and restrictions throughout the year. In August 2010, the State Council set up an inspection team to inspect 18 key areas such as Zhejiang and Hebei to carry out special inspections on energy saving and emission reduction. In order to achieve the "11th Five-Year Plan" energy-saving and emission-reduction targets, Zhejiang, Hebei, Shandong, and Shanxi provinces, among other areas, began to pull the plug on electricity. The year 2021 saw a high increase in industrial electricity consumption driven by continued export growth, as well as a large increase in residential electricity demand due to weather factors and the demand for charging new energy vehicles. In addition, in the first half of 2021, some provinces failed to meet their energy consumption targets, and under the pressure of policy targets, Guangxi, Guangdong, and Anhui implemented phased electricity restrictions, while Shaanxi and Yunnan implemented production restrictions on the "two high" industries.

Although the number of power outages at the beginning of the century was historic, power shortages remain a major problem in China. The unreliability of electricity supply is not only a major threat to the stability of manufacturing firms' production processes, but it is also an obstacle to the expansion of manufacturing firms' production. This paper therefore seeks to explore how energy poverty in the form of electricity shortages affects the productivity of manufacturing firms in China. In particular, the relationship between electricity shortage and the technical efficiency of manufacturing firms is examined using panel data from 805 listed manufacturing firms in China for the period 2009–2020. This turns out to be in contrast with the vast literature associated with the analysis of electricity shortages in African and South Asian countries. Therefore, the application to China will add insights to the research on electricity shortages and productivity, arising from the relatively large number of manufacturing firms in China, the huge demand for electricity, and the large number of publicly owned companies compared to most African and Asian countries.

To achieve the objectives of this study, a two-stage analysis approach was adopted using data from the CSMAR database. In the first stage, the stochastic frontier approach (SFA) was used to calculate the technical efficiency (TE) of the manufacturing firms under consideration. This was then used as the main dependent variable in the regression analysis in the second stage to evaluate other factors that affect the technical efficiency of manufacturing firms, including electricity shortages.

The rest of the paper is structured as follows: Section 2 provides a review of the relevant literature. Section 3 describes the research strategy and empirical model. Section 4 briefly presents the data. Section 5 presents and discusses the empirical results and the final section concludes the paper and provides policy implications.

2. Review of the Literature

The measurement of technical efficiency is one of the core elements of the study of enterprise technology management. Technical efficiency is used to measure the distance between the actual level of output of a firm and the maximum amount of output that can be achieved given an equal number of factor inputs; the greater the distance, the lower the technical efficiency. Technical efficiency reflects a firm's ability to make optimal use of the available resources. In terms of technical efficiency measurement methods, parametric and non-parametric methods are the main methods used by Chinese scholars in measuring technical efficiency, among which the stochastic frontier analysis (SFA) and Data Envelopment Analysis (DEA) are most commonly used. These methods solve the problems by introducing a random variable that represents statistical noise. The SFA method is also able to analyze the panel data and provide a richer representation of the longitudinal and cross-sectional comparative relationships of the groups under study.

In recent years, a number of papers have been published in Chinese that tend to use SFA when dealing with the technical efficiency of listed companies, which often face complex stochastic environments. These studies point to the evidence of significant technical inefficiency among the listed companies in China, which differ depending on the level of carbon intensity.

With regard to electricity shortages and firm productivity, the literature has focused mainly on the African region and South Asia [3], specifically studying the severe power outages in sub-Saharan Africa. They highlight that power outages negatively affect firms' production, further limiting the development of the local economy. Ref. [4] investigates the relationship between power outages and the technical efficiency of firms. The study used 2755 manufacturing and service industries from 10 countries in Africa. The extent of the power interruptions was measured by the frequency of the power interruptions and based on a stochastic frontier approach (SFA); the findings revealed that the number of power outages in a typical month for African firms has a significantly negative impact on a firm's productivity. The authors also suggest that the negative impact of frequent power outages on firm productivity may discourage foreign investors from investing in Africa. Ref. [5] further investigated the impact of power interruptions on the sales performance of manufacturing firms in sub-Saharan Africa. Their study used data on firms from 14 countries in sub-Saharan Africa from the WBES database. The findings suggest that power outages have a significantly negative impact on the annual sales and productivity of manufacturing firms. Ref. [6] investigates the impact of power outages on the productivity of SMEs using a sample from a single African country, Senegal. The extent of power outages is measured by the frequency and average duration of the power outages. In addition, the study uses a stochastic frontier approach. Outputs and inputs correspond to the value added, capital, and employment, respectively. The study showed that manufacturing firms in Senegal lost about 15% of their productivity due to the disruption caused by power outages. The key finding of this study is that power outages have a significantly negative impact on the productivity of manufacturing firms in Senegal.

For Asian countries, Ref. [7] examines the relationship between energy poverty and economic development in South Asia. The authors used panel data from all seven countries in South Asia. The study shows that underdeveloped electricity infrastructure and a lack of modern energy sources have a significantly negative impact on economic development in South Asia. Ref. [8] focuses their study on firms in the manufacturing sector in the MENA region. The performance of manufacturing firms was measured by three indicators: annual sales growth rate, annual employment rate, and annual labor productivity growth rate. The results of the study indicate that power disruptions have a significantly negative impact on the business performance of manufacturing firms.

For China in particular, studies on power shortages and firm productivity are scarce. A notable exception is [9], who surveyed 23,000 energy-intensive Chinese firms between 1999 and 2004 to examine how firms cope with severe power shortages. The findings suggest that in response to power shortages, Chinese firms have re-optimized production inputs by substituting materials for energy (both electricity and non-electricity sources), i.e., shifting from 'manufacturing' to 'buying' production intermediate inputs.

3. Research Methodology

3.1. Model Choice

The aim of this study is to examine the impact of electricity shortages on the technical efficiency of manufacturing firms; we have used a two-stage analysis in our research strategy.

There are two methods of measuring technical efficiency based on the production frontier surface: parametric and non-parametric methods. Both methods involve the estimation of the frontier surface for the construction of the optimal economic unit and the relative distance of a specific economic unit from the frontier surface. Parametric methods, also known as econometric methods, set specific cost functions, profit functions, and production frontiers, and they are stochastic methods. The reason why economic units do not fall on the production frontier, i.e., the firm does not achieve maximum output, may be because they are inherently inefficient, or may be due to random errors or measurement errors. Parametric methods include stochastic frontier methods (SFA), distribution-free methods (DFA), and thick frontier methods (TFA). Non-parametric methods, also known as mathematical methods, include Data Envelopment Analysis (DEA) and Free Disposition Hull (FDH) methods. Non-parametric methods make no assumptions about the specific form of the production function, they have little discussion of the frontier surface, they are non-random, and any distance from the frontier surface is considered to be invalid.

It is generally believed that the SFA-based parametric approach has the following advantages over the nonparametric approach: φ The parametric approach takes into account the luck component, data problems, or other stochastic errors caused by measurement problems, compared to, for example, the nonparametric approach, which attributes the entire distance of actual output from the frontier to inefficiency, which would appear to be biased when studying the technical efficiency of manufacturing firms. SFAκ can facilitate testing the significance of the results. The dispersion of efficiency values estimated by SFAλ is relatively small. In addition, non-parametric methods generally ignore prices and therefore can only explain the inefficiency of technologies that use too many or too few outputs. The problem with nonparametric methods is that the above errors in any sample observation on the efficiency frontier have the effect of affecting the accuracy of the efficiency frontier and thus changing the efficiency values of all other sample points. Generally speaking, nonparametric methods focus on technical optimality rather than economic optimality. Therefore, in this paper, parametric methods are used when studying the technical efficiency of manufacturing firms.

The non-parametric methods are stochastic frontier approach (SFA), distribution-free approach (DFA), and thick frontier approach (TFA). TFA assumes that the variance within the group of decision units is random error and the variance between the group of decision units is inefficient; DFA assumes that the technical efficiency of each decision unit is stable over time and the random error terms can cancel each other out. DFA and TFA are both special forms, and most of the literature also uses SFA method to measure efficiency; so, this paper chooses the mature parametric method SFA.

3.2. Theoretical Framework for Technical Efficiency Measures

The technical efficiency of an enterprise is the level of output that the enterprise can actually achieve with a given amount of inputs. It is a measure of the productive capacity of a firm. There are two main methods that are used in most of the literature to calculate the technical efficiency value of a manufacturing firm. The first is a deterministic model which, although it can be used to measure the productivity of a firm, has the obvious disadvantage of treating any deviation from the firm's theoretical maximum output as the result of technical inefficiency, in which case, the difference between the firm's actual level of output and its theoretical maximum level of production is attributed to the inefficiency of the firm.

The second model is a non-deterministic stochastic model. One popular and widely used approach is the SFA model, which does not treat all deviations from the production frontier as the result of a firm's technical inefficiency. It assumes that some of the deviations are random and that the SFA takes into account the effect of measurement and data errors on the technical inefficiency of the firm.

3.3. Measuring Technical Efficiency with Stochastic Frontier Analysis

The SFA model provides an estimate of the technical efficiency of the decision unit by decomposing the error term into two components, one representing random error and the other representing technical inefficiency. The model form is as follows:

$$Y_{it}= \beta X_{it} + (v_{it} - u_{it}) \tag{1}$$

where Y_{it} in Equation (1) is the output of the firm i in year t, X_{it} is the input variable of the firm i in year t, β is an unknown parameter variable, v_{it} is a random variable and independent of u_{it}, and u_{it} is a non-negative random variable that accounts for the technical inefficiency of production.

According to the definition of efficiency by [10], technical efficiency can be expressed as the following:

$$Te_{it}=\frac{E(Y_{it}|u_{it},X_{it},t=1,2,\ldots\ldots,T)}{E(Y_{it}|u_{it}=0,X_{it},t=1,2,\ldots\ldots,T)}=\frac{exp(\beta X_{it}-u_{it})}{exp(\beta X_{it})}=exp(-u_{it}) \tag{2}$$

Technical efficiency takes values from 0 to 1. If a firm has a technical efficiency value of 1, then the firm is fully efficient. Based on the SFA, we can calculate the technical efficiency values for manufacturing firms and then use these estimates in the second stage of the analysis.

3.4. Regression Model in Second Stage

In the second stage of the analysis, the values of TE derived from the first stage of the analysis are regressed on the other determinants of technical efficiency of manufacturing firms. Considering that the main objective of this study is to examine the impact of electricity shortage on the technical efficiency of manufacturing firms, the second stage regression model is expressed as follows:

$$\begin{aligned} Te_{it} &= \beta_0+\beta_1 E\_outages_{it}+\beta_2 intangible\_assets_{it}+\beta_3 total\_assets_{it}+ \\ &\beta_4 Listing\_years_{it}+\beta_5 Executive\_salary_{it}+u_{it} \end{aligned} \tag{3}$$

where Te_{it} denotes the technical efficiency of firm i in year t. β is the variable parameter, u_{it} is the random error term, and $E\_outages_{it}$ denotes electricity shortage, as measured by the ratio of generation to capacity of thermal power plants in the China Electricity Yearbook, chosen with reference to Karen Fisher-Vanden (2015). Based on the relevant literature, this paper uses net intangible assets ($intangible\_assets_{it}$), net total assets ($total\_assets_{it}$), years of listing ($Listing\_years_{it}$), and executive salaries ($Executive\_salary$) as control variables.

To address any endogeneity problem due to reverse spillover and other reasons, this paper attempts to construct a heat capacity factor (rrl) lagging one period as an instrumental variable for electricity shortage, where the previous period of the endogenous variable is not correlated with the current period error term and has exogeneity. Meanwhile, the lagged one-period rrl has a correlation with the current period rrl.

$$\begin{aligned} Te_{it} &= \beta_0+\beta_1 E\_outages_{it-1}+\beta_2 intangible\_assets_{it}+\beta_3 total\_assets_{it}+ \\ &\beta_4 Listing\_years_{it}+\beta_5 Executive\_salary_{it}+u_{it} \end{aligned} \tag{4}$$

4. Data

4.1. Technical Efficiency Measurements

In the theoretical framework of technology measurement, Y_{it} and X_{it} represent input and output, respectively. According to the existing literature, most of the output is chosen by the operating income indicator, and some of the literature is chosen by the operating profit indicator, but considering that operating profit may be negative and operating profit may be subject to artificial control, large listed companies may transfer profits through related transactions, which are more objective compared to the operating income, so this paper chooses the operating income indicator to represent enterprise output. The data were obtained from the annual reports of listed companies. In terms of input, capital input and human input are mainly considered, among which capital input is chosen as net fixed assets and the total number of employees at the end of the year is taken as the indicator of labor input.

4.2. Technical Efficiency Impact Factor Indicators

The technical efficiency of manufacturing firms is influenced by multiple factors, and in this paper, intangible assets, firm size, age at IPO, and executive pay are chosen as control variables.

Intangible assets, which embody a right or the ability to earn excess profits, may have an impact on the technical efficiency of manufacturing firms. In contrast, being in the market for a long time will give the company certain financing advantages, management advantages, and first-mover advantages in the energy sector, which will make the company more competitive and more efficient, thus increasing the technical efficiency of the company. Increasing executive compensation will result in higher inputs, while incentives for executives will not result in a correspondingly higher or lesser increase in output, so increasing executive compensation decreases the technical efficiency value of the firm. Increase in firm size, expressed as total firm assets, will make it more competitive and, therefore, more profitable and economically efficient. On the other hand, an increase in the size of the company leads to economies of scale, a rise in the utilization of existing resources, and an increase in technical efficiency.

4.3. Data Sources

The production data in this paper were obtained from the financial statements and governance structure of listed companies in the CSMAR database, selecting all A shares and excluding ST shares, and manufacturing data according to the 2012 edition of the industry classification of the Securities and Futures Commission. Because of the revision of the Chinese accounting system in 2009, this paper selects data from 2009 to 2020 for the sake of data comparability. Electricity data were obtained from the China Electricity Statistical Yearbook, and technical efficiency data were calculated by the software Frontier. After eliminating missing data and non-comparable data, a total of 805 listed manufacturing enterprises were obtained. Table 1 shows the data interpretation and sources.

Table 1. Variable interpretation and sources.

Variable	Variable Symbol	Variable Interpretation	Data Source
Technical efficiency	Te	Technical efficiency of SFA estimates	Calculated by Frontier software
Capital inputs	Capital	Net fixed assets	CSMAR Database
Labor input	Labor	Number of full time employees at the end of the year	CSMAR Database
Power shortage	rrl	Ratio of generation to capacity of thermal power plants (heat capacity factor)	China Electricity Statistical Yearbook
Excess profitability	wxzc	Net intangible assets	CSMAR Database
Company size	zzc	Total company assets	CSMAR Database
Age at listing	ssnx	Number of years that the company has been listed	CSMAR Database
Executive salary	ggxz	Senior management salaries	CSMAR Database

Source: Compiled from China Electricity Statistical Yearbook and CSMAR database.

5. Empirical Results and Discussion

5.1. Descriptive Statistics

Table 2 presents the descriptive statistics of the variables of interest. The observations are filtered panel data of 805 Chinese listed manufacturing firms for a total of 12 years from 2009 to 2020, with a total of 9660 observations. Te and rrl denote the technical efficiency and heat capacity factors, respectively, lnCapital, lnLabor, lnwxzc, lnzzc, and lnggxz denote the logarithmic results of the input capital, labor, corporate intangible assets, total assets, and executive salaries, respectively, and ssnx denotes the number of years tgar the control variable has been listed. Logs of most of the variables have been taken to stabilize variances and improve the estimation properties of the data [11]. The results of the descriptive statistics give a preliminary indication of the broad trends in the variables of interest.

Table 2. Descriptive statistics of relevant variables.

Variable Name	Observed	Mean	Standard Deviation	Min	Max
Te	9660	0.918	0.0293	0.743	1.000
rrl	9660	0.437	0.0735	0.00732	0.596
lnCapital	9660	20.64	1.517	13.11	26.14
lnLabor	9660	8.012	1.192	2.890	12.29
lnwxzc	9660	2.932	0.0874	1.959	3.176
lnzzc	9660	22.23	1.286	17.05	27.55
ssnx	9660	19.64	5.151	11	31
lnggxz	9660	14.79	0.903	10.09	18.42

5.2. Regression Results Based on OLS Estimation

The second stage of the regression of the technical efficiency values calculated by the SFA method was based on several expected influencing factors, so before conducting the baseline regression analysis, the paper first performed a test for multicollinearity. This paper uses VIF to rigorously test for multicollinearity, and Table 3 shows the results of the VIF test, which indicate that the VIFs of the variables are all less than 10, indicating that there is no multicollinearity between the variables.

Table 3. Variance inflation factors.

Variable	VIF	1/VIF
lnzzc	3.220	0.310
lnwxzc	2.800	0.357
lnggxz	1.460	0.687
ssnx	1.060	0.946
rrl	1.030	0.969
Mean	VIF	1.910

Before doing the benchmark regression analysis, according to the Hausman test, the p-value was less than 0.01, the original hypothesis was rejected, and a fixed effects model was used, so the individual fixed effects model was used in this paper. Considering that the unobserved data of each listed company may be relevant, this paper clustered the standard errors at the company level. The baseline regression results based on the ordinary least squares (OLS) estimation in Equation (3) are shown in Table 4. Column 1 of the table shows the results of the regressions on the technical efficiency of listed manufacturing firms and the heat capacity factor representing a power shortage, and the results indicate that they pass the test at the 1% level of significance. Column 2 adds logarithmic intangibles to the regression and also yields a statistically significant test result at the 1% significance level. The same test results were obtained after successively adding logarithmic total assets, logarithmic years on market, and logarithmic executive salary data, the detailed results of which are shown in columns 3–5 of Table 4.

The results in Table 4 show that the thermal capacity factor, which is used to measure electricity shortage, is statistically significant at the 1% level of significance. The correlation coefficient is negative, and the thermal capacity factor is expressed in terms of the thermal power generation and installed capacity in the China Electricity Statistical Yearbook, where the ratio of thermal power generated to the thermal power capacity is used as a measure of electricity scarcity. Given our research questions, we are most interested in the response of firms to the threat of electricity scarcity, regardless of whether or not a blackout actually occurs. Whereas a larger heat capacity factor indicates a larger share of already utilized electricity resources and a smaller share of remaining available e-resources, the more severe the electricity shortage. The results show that the coefficient of the heat capacity factor is significantly negative, indicating that a power shortage has a negative impact on the technical efficiency of listed manufacturing companies in China. According to columns 2–5 of Table 4, after considering the various variables, it is still statistically significant at the 1%

level of significance, and the coefficient is also negative, which is similar to the previous results. Therefore, from the OLS regression, it can be concluded that the electricity shortage has a significantly negative impact on the technical efficiency of the listed manufacturing firms in China. The results of the OLS analysis with the recent Chinese data are consistent with the previous research, which utilizes much older data for China [9].

Table 4. Baseline regression results based on OLS estimation.

	(1)	(2)	(3)	(4)	(5)
Variables	**Te**	**Te**	**Te**	**Te**	**Te**
rrl	−0.066 ***	−0.056 ***	−0.044 ***	−0.044 ***	−0.040 ***
	(−40.94)	(−29.75)	(−22.39)	(−22.39)	(−22.28)
lnwxzc		0.002 ***	−0.000	−0.000	−0.000
		(12.30)	(−0.52)	(−0.52)	(−0.57)
lnzzc			0.005 ***	0.005 ***	0.003 ***
			(16.21)	(16.21)	(10.45)
o.lnssnx				-	-
lnggxz					0.003 ***
					(15.58)
Constant	0.947 ***	0.905 ***	0.831 ***	0.831 ***	0.817 ***
	(1348.44)	(256.26)	(142.25)	(142.25)	(153.97)
Observations	9660	9660	9660	9660	9660
R-squared	0.973	0.976	0.980	0.980	0.982
Fixed effect	Yes	Yes	Yes	Yes	Yes

*** Indicates significance of the coefficient at the 1% level.

For the control variables, the results were partially expected to be largely consistent in the previous section. For example, the inclusion of total assets, representing firm size, in column 3 of Table 4 leads to the conclusion that the effect of firm size is positive and passes the test at the 1% level of significance. Combining the results in Table 4 shows that larger firms can reduce the negative impact of outages on the TE to some extent, while smaller firms tend to fail to mitigate the negative impact of outages on the TE. This suggests that listed manufacturing companies are at a stage of development where an increase in the company size can increase the competitiveness of the company and therefore encourage higher profits. An increase in company size also allows for economies of scale to emerge and for the company to become more technically efficient. However, it can be seen from the results that the impact of the company's excess profitability on the technical efficiency is not significant, probably because the formation of intangible assets, including patents, mainly comes from the capitalization of R&D costs, and as the company increases its R&D investment, the total cost of the company rises, and the formation of intangible assets does not happen overnight, thus making the improvement in technical efficiency not immediately apparent. The technical efficiency of China's listed manufacturing companies is not related to the length of time the companies have been listed. The length of time that the companies have been listed is not necessarily related to their technical efficiency, as earlier listing means more experience accumulation on the one hand, and on the other hand, it may also mean that the technical equipment and management concepts are backward. The effect of executive pay on the technical efficiency of listed manufacturing companies is positive and statistically significant at the 1% level of significance. The quality of employees is the basis of a company's competitiveness and determines the technical and managerial level of the company. Highly qualified personnel are very scarce, so vigorously training, introducing, and using well-qualified personnel becomes the key to improving technical efficiency. Increasing executive salaries can effectively attract and retain talent, thus building a team of highly qualified personnel and improving the technical efficiency of the company.

5.3. Robustness Tests

In order to test the credibility of the results, when using the SFA model to calculate the technical efficiency of companies, in addition to labor and capital inputs, raw material input indicators were added, expressed as operating costs in the income statements of listed manufacturing companies; the results obtained are shown in Table 5.

Table 5. Robustness tests.

Variables	Te
rrl	−0.009 ***
	(−26.26)
lnwxzc	−0.000
	(−0.52)
lnssnx	-
lnzzc	0.001 ***
	(12.18)
lnggxz	0.001 ***
	(16.56)
Constant	0.917 ***
	(811.61)
Observations	9660
Number of id	805
R-squared	0.995
Fixed effect	Yes

*** Indicates significance of the coefficient at the 1% level.

From the regression estimation results, the correlation coefficient between the heat capacity factor, representing the electricity shortage, and the technical efficiency of the firm is −0.009, which is statistically significant at the 1% level of significance, and the results have a statistically significant negative sign. The above findings are consistent with the previous results and are therefore robust to the conclusion that electricity shortages have a negative impact on the technical efficiency of manufacturing firms. The results in Table 5 show that the four control variables also show the expected signs. Overall, the results of the model are generally consistent with the results of the prior benchmark regression. Therefore, the results of this study are robust and consistent.

5.4. Heterogeneity Analysis Based on OLS Regression

The sample typically involves time-series data (2009–2020 for each manufacturing firm). Therefore, diagnostic tests for unobserved heterogeneity should be considered to ensure a good model fit. The analysis of unobserved heterogeneity was increased by distinguishing the nature of companies into state-owned and non-state-owned companies, and by classifying companies into large-scale, medium-sized, and small-scale companies from the size of manufacturing companies to study heterogeneity.

The results of the heterogeneity analysis based on the nature of enterprise ownership and enterprise scale are presented in Tables 6 and 7, respectively. These results show that both firm ownership and firm size affect the relationship between technical efficiency and power shortages, indicating that state-owned companies and large-scale firms may be able to cope with power shortages by increasing their capital investment and reducing raw material inputs, such as electricity, or "self-generation", because of their strong capital strength. On the contrary, privately owned and small- and medium-size companies are more likely to be negatively affected by electricity shortages, which is consistent with the baseline regression.

Table 6. Heterogeneity analysis on the nature of enterprise ownership based on OLS.

	(1)	(2)
Variables	**GQ**	**FGQ**
rrlState_GQ	0.043 ***	
	(5.29)	
lnwxzc	−0.009 ***	−0.009 ***
	(−6.70)	(−6.48)
lnzzc	−0.003	−0.002
	(−1.53)	(−0.79)
lnggxz	0.011 ***	0.012 ***
	(7.29)	(7.57)
rrlState_FGQ		0.059 ***
		(10.84)
Constant	0.857 ***	0.778 ***
	(30.59)	(26.29)
Observations	9528	9540
R-squared	0.210	0.219
Individual fixed effects	Yes	Yes

*** Indicates significance of the coefficient at the 1% level.

Table 7. Heterogeneity analysis on enterprise scale based on OLS.

	(1)	(2)	(3)
Variables	**Large**	**Middle**	**Small**
rrlScale_L	0.029 ***		
	(4.45)		
lnwxzc	−0.010 ***	−0.010 ***	−0.010 ***
	(−6.79)	(−6.87)	(−6.95)
lnzzc	−0.006 ***	−0.003	0.002
	(−2.79)	(−1.49)	(0.99)
lnggxz	0.010 ***	0.010 ***	0.011 ***
	(7.06)	(7.07)	(7.33)
rrlScale_M		−0.007 *	
		(−1.65)	
rrlScale_S			0.035 ***
			(5.61)
Constant	0.950 ***	0.884 ***	0.755 ***
	(29.55)	(33.02)	(21.44)
Observations	9660	9660	9660
R-squared	0.213	0.212	0.215
Individual fixed effects	Yes	Yes	Yes

*** Indicates significance of the coefficient at the 1% level. * Indicates significance of the coefficient at the 10% level.

5.5. Regression Results Based on the Instrumental Variable (IV) Estimation

When the IV estimation approach is adopted to address endogeneity issues in the data, the results appear to be significantly different from the OLS regression. The baseline regression using IV, as presented in Table 8, shows that the heat capacity coefficient used to measure electricity shortages is statistically significant at the 1% level of significance. Compared to OLS, the instrumental variables yield different findings with positive correlation coefficients, where the ratio of thermal generation to thermal generation is used as a measure of electricity shortages. Contrary to the OLS regression, these results show that the coefficient of the heat capacity factor is significantly positive, indicating that there is a dynamic endogeneity problem in the panel data, and the conclusions drawn using instrumental variables indicate that power shortages have a positive effect on the technical efficiency of Chinese manufacturing listed companies. According to columns 2–5 of Table 4, the coefficients are still statistically significant and positive at the 1% significance level after considering other control variables. This positive relationship can be attributed to the positive impact of firm's responses to electricity shortages, which tend to offset the adverse effects of power shortages. The results of the IV regression in this study are different from previous studies in the literature [3–8], and we suggest that the results of previous studies based on OLS regression should be treated with care. In terms of the control variables, most of the results are consistent with the OLS regression.

Table 8. Baseline regression results based on IV estimation.

	(1)	(2)	(3)	(4)	(5)
Variables	**Te**	**Te**	**Te**	**Te**	**Te**
rrl	0.00045 ***	0.00043 ***	0.00046 ***	0.00046 ***	0.00045 ***
	(3.04)	(2.89)	(3.14)	(3.14)	(3.07)
lnwxzc		−0.00004 ***	−0.00001 ***	−0.00001 ***	−0.00001 ***
		(−9.95)	(−2.79)	(−2.79)	(−2.84)
lnzzc			−0.00008 ***	−0.00008 ***	−0.00009 ***
			(−8.64)	(−8.64)	(−9.38)
o.lnssnx				-	-
lnggxz					0.00003 ***
					(4.18)
Observations	8855	8855	8855	8855	8855
R-squared	0.967	0.968	0.968	0.968	0.969
Number of id	805	805	805	805	805
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes

*** Indicates significance of the coefficient at the 1% level.

5.6. Heterogeneity Analysis Based on IV Regression

The results of the heterogeneity analysis based on the nature of a firm's ownership and size under IV estimation are shown in Tables 9 and 10, respectively. Again, contrary to the OLS regression, the heterogeneity analysis under IV estimation suggests that while size may have no bearing, state-owned companies are more likely to be adversely affected by electricity shortages.

Table 9. Heterogeneity analysis on the nature of enterprise ownership based on IV regression.

	(1)	(2)
Variables	**Te**	**Te**
rrlState_GQ	−0.00012 *	
	(−1.86)	
rrlState_FGQ		−0.00005
		(−0.78)
lnwxzc	−0.00001 ***	−0.00001 ***
	(−2.91)	(−2.91)
lnzzc	−0.00008 ***	−0.00008 ***
	(−8.84)	(−8.95)
o.lnssnx	-	-
lnggxz	0.00003 ***	0.00003 ***
	(3.98)	(4.05)
Observations	8734	8734
R-squared	0.969	0.969
Number of id	794	794
Time fixed effects	Yes	Yes
Individual fixed effects	Yes	Yes

*** Indicates significance of the coefficient at the 1% level. * Indicates significance of the coefficient at the 10% level.

Table 10. Heterogeneity analysis on enterprise scale based on Iv regression.

	(1)	(2)	(3)
Variables	**L**	**M**	**S**
rrlScale_L	0.00001		
	(0.29)		
rrlScale_M		0.00004	
		(1.30)	
rrlScale_S			−0.00004
			(−0.95)
lnwxzc	−0.00001 ***	−0.00001 ***	−0.00001 ***
	(−2.85)	(−2.81)	(−2.75)
lnzzc	−0.00009 ***	−0.00009 ***	−0.00009 ***
	(−7.99)	(−9.38)	(−7.59)
o.lnssnx	-	-	-
lnggxz	0.00003 ***	0.00003 ***	0.00003 ***
	(4.27)	(4.27)	(4.26)
Observations	8855	8855	8855
R-squared	0.969	0.969	0.969
Number of id	805	805	805
Time fixed effects	YES	YES	YES
Individual fixed effects	YES	YES	YES

*** Indicates significance of the coefficient at the 1% level.

6. Conclusions and Policy Implications

This study evaluates the impact of power shortages on the technical efficiency of listed manufacturing companies in China, based on firm-level data provided by CSMAR. The analysis process can be divided into two stages. In the first stage of the analysis, SFA was used to estimate the technical efficiency values of manufacturing firms. In the second stage, the technical efficiency scores of manufacturing firms were regressed on the factors that were expected to affect the technical efficiency of the firms. Two estimation methods have been adopted, including OLS, which does not account for the endogeneity, and IV estimation, which turns out to be more robust to endogeneity in the data. The following conclusions were drawn.

First, the empirical results indicate that, under OLS estimation, electricity shortages have a significantly negative impact on the technical efficiency of manufacturing firms. However, when IV regression is implemented to address endogeneity issues in the data, electricity shortages tend to have a significant positive impact on the technical efficiency of manufacturing firms. This positive relationship is attributed to the positive impact of enterprise responses to electricity shortages, which may have an offsetting effect on electricity shortages. Further analysis reveals that, while the size of enterprises may have no bearing, state-owned companies are more likely to be negatively affected by electricity shortages compared to privately owned companies.

Second, our findings also suggest that executive pay has a positive impact on improving the technical efficiency of firms. In contrast, firm excess profitability and the number of years that a firm has been on the market do not have a significant effect on technical efficiency.

The technical efficiency of traditional manufacturing firms depends mainly on the productivity of workers. With the development of modern mechanization, machines are much more efficient than manual production. Electricity is the most common source of energy for mechanized production lines. However, China still faces a shortage of electricity, which reduces sustained production activity. In some highly mechanized manufacturing enterprises, if machines stop working due to power outages, workers are unable to continue working. This may widen the gap between the actual output and the theoretical maximum output of the firm, thus leading to a deterioration in the technical efficiency of the manufacturing firm. From our findings, it is clear that electricity shortages directly and significantly affect the technical efficiency of manufacturing firms in a far-reaching way. Furthermore, considering that manufacturing firms are an integral part of the local economy, they are directly related to the income of local people and the development of the local economy. In the long run, frequent power outages will have a negative impact on workers' incomes and the local economy.

The findings of this paper can provide some basis for listed manufacturing companies to be aware of the importance of electricity and to develop appropriate measures to deal with power shortages. Businesses are the backbone of the economy. Progress in business is progress in the economy. As businesses flourish, they create more jobs, provide better services and goods, create greater investment and production expansion, and generate more tax revenue for the government. Therefore, a focus on the factors in the economy that affect business is essentially a focus on the health of the economy. In the 21st century, an important factor in the production of inputs for businesses is energy [12,13]. Energy brings together other factors of production and increases the efficiency of those factors. It also provides some incentive for manufacturing companies to reduce the impact of power shortages in various ways, for example, [9] concludes that manufacturing companies can reduce corporate production costs and cope with power shortages by outsourcing to increase productivity. Most importantly, the results of this study underscore the importance of policies and measures to promote a shift in ownership structure towards the private sector.

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