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## Article

# Analysis of industrial transformation and upgrading in resource-exhausted cities: evidence from city-level and enterprise-level panel data

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**Abstract.** Massive and irrational exploitation of natural resources promoted the industrialization process, which formed different categories of resource-based cities. Although these cities have made dramatic contributions to socio-economic development in the last two decades, they are now facing grave problems due to resource depletion. Industrial transformation and upgrading are the only ways to cope with this situation. Therefore, this study utilizes the city-level and enterprise-level data to analyze the industrial transformation and upgrading of resource-exhausted cities in China. Both the macro- and micro-empirical results demonstrate that the central policy of the State Council has a positive feedback on industrial transformation. Then the findings of baseline regression are validated by robustness and heterogeneity tests. What's more, the policy facilitates industrial upgrading by promoting transition to technology-intensive and high-value chain industries. Finally, we propose relevant implications for industrial transformation on the basis of the main findings.

**Keywords:** resource-exhausted city; industrial transformation; industrial upgrading; optimization of industrial structure.

**JEL classification:** O25, Q32, R11

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## 1. Introduction

China is a vast territory with many cities where resource industry is their most important economy's mainstay. The type of city is a resource-based city, which played a prominent role in the industrialization process. They contributed to advancing regional economic development and solving the social problem of employment (Zhang et al. 2018). However, resource-based cities have a distinct character of the industry life cycle. They develop rapidly in the early stages due to their resource advantages, but eventually, they turn into resource-exhausted cities owing to resource depletion. When the resource advantages no longer exist, those cities struggle to overcome many difficulties of economy and environment (Wang et al. 2019). This situation makes a resource-exhausted city the top priority in the regional development.

In recent years, a small minority of resource-exhausted cities made some headway in industrial transformation after unceasing exploration. However, many resource-exhausted cities still confront difficult situations, such as insufficient internal impetus for transformation and development, sluggish economy, severe ecological damage, and so on. How to solve these problems is a major concern of the whole country. The State Council issued an official document<sup>1</sup> and announced 69 regions as resource-exhausted cities in 2008, 2009, and 2011. Once identified as a resource-exhausted city, the central government will provide general transfer payments to support this city. The official document is intended to support industrial restructuring, upgrading, and sustainable development. On the one hand, the experience of transformation of those cities could provide practical implications for regional development; on the other hand, it could also provide experience for high-quality economic growth of the whole country. It is not only a crucial factor of economic development but also the top priority for a harmonious society.

The industrial transformation and upgrading are the only correct solutions to the problems of resource-exhausted cities, which is emphasized in the official guidance document. Industrial development is associated with the grand macroeconomic plans of the state economy (Lin and Zhu 2021). Analyzing the industrial development has important implications for exploring the targeted supporting strategies. Constant changes in the leading industry have promoted the transformation and optimization of the industrial structure in the process of economic development. The most important task of transformation is to optimize the proportion of various industries and promote the transition from labor-intensive and resource-intensive to technology-intensive industry (Wang et al. 2019). There are numerous researchers who concentrate on industrial transformation and upgrading because of their great prospects, generating many valuable results. Some researchers have employed metrics such as the share of manufacturing in GDP or the percentage change in clean and polluting industries to measure the level of industrial upgrading (Cheng, Li, and Liu 2018; Cole 2000; Du, Cheng, and Yao 2021). Others have concentrated on technological progress and its role in upgrading. Technological advancement serves as a vital driver of industrial upgrading, directly influencing productivity (Ngai & Pissarides 2007; Raymond et al., 2015; Wang et al., 2022). Empirical analyses can be categorized based on data sources: one category involves micro-level provincial or city-level data, while the other involves micro-enterprises. After comprehensively studying and fully clarifying the existing literature, we found these two obvious characteristics. (1) The majority of existing studies use city-level data or provincial-level data to explore the current situation and future development trends of resource-exhausted cities. However, as industrialization advances, the development of industrial enterprises should be a better indicator of the national economy. (2) Among all studies concerning the transformation of resource-exhausted cities, many scholars have utilized various traditional methods (e.g., Solow residual) to measure the industrial development (Solow 1957). However, this traditional method is more suitable for macroeconomic analysis.

Thus, in order to overcome the shortcomings of these two aspects, we make corresponding improvements. (1) First, this paper intends to explore the industrial transformation and upgrading from both macro city-level and micro enterprise-level in resource-exhausted cities. On the one hand, we can observe whether the transformation strategies of micro enterprises are in line with the

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<sup>1</sup> The State Council issued the official document named Opinions for Promoting the Sustainable Development of Resource-based Cities.

overall direction of macro industrial structure adjustment by combining macro and micro level data; On the other hand, we can deeply analyze the essence behind macro industrial phenomena by combining macro and micro level data. (2) Second, using firm-level data from 2005-2013, this paper applies the total factor productivity calculated by LP method (Levinsohn and Petrin 2003) to assess the level of industrial transformation. The LP method is well known for its introduction of intermediate input as the proxy variable and therefore would effectively mitigate the data missing problem.

For the remainder of this study, we will conduct a comprehensive and detailed analysis. The specific arrangements are as follows: The second section recapitulates related literature. Section 3 expounds the empirical model and the data resource. In Section 4, we provide a detailed analysis of preliminary regression results. Section 5 further validates the baseline regression by robustness and heterogeneous tests. The mechanism analysis of industrial transformation is conducted in Section 6. The last section sums up the main conclusions and proposes corresponding implications.

## **2. Literature review and hypothesis**

### **2.1 Literature review**

A lot of scholars conducted extensive research on industrial transformation. In this part, we comprehensively classify and illustrate the existing literature on the development status, future prospects, and transformation of resource-based cities.

(1) Resource-based city. Numerous studies have been conducted on the relationship between resource endowment and economics since the 1990s. In 1994, Auty proposed a counterintuitive theory named the resource curse theory. He found that the countries with poorer resource endowments have industrialized more successfully than resource-abundant countries. Thereafter, many scholars committed to analyzing the issue of the resource curse. Based on the definition of the resource curse, Sachs and Warner published articles on the resource curse in 1995, 1997, and 1999, which laid an important foundation for subsequent research by many scholars (Sachs and Warner, 1995; 1997; 1999). Cockx and Francken (2014) wondered if natural resource dependence would have any impact on a country's public health expenditures. Ultimately, based on the results of countries around the world, they found a significant inverse relationship between resource dependence and public health expenditure. Furthermore, they argued that the natural resources in one country should be planned by the government. Smith (2015) found a long-run sustained positive impact on GDP per capita after resource exploitation with a fixed-effect empirical model. In addition, this effect exhibits obvious heterogeneous characteristics between OECD and non-OECD treatment countries.

Also, many researchers have analyzed the major determinants of development in resource-based cities. According to Yu et al. (2008), the development of 78 mining cities in China was found to be related to the geographical location and the natural resource types. Li et al. (2013) conducted an analysis and concluded that resource-based cities usually had a slower pace of development than other cities. They argued that the possible cause was the consequence of a planned economy, specifically, an unreasonable taxation system, an unsuitable plan, and an inappropriate policy of

resource development. Apart from the influencing factors, the serious consequences also involved. Ploeg (2010) investigated whether resource has economic and social impacts. He identified a number of negative impacts, including exchange rate appreciation, slower growth prospects, internal conflicts, corruption, and so on. There are also studies on the transformation of resource-based cities abroad. Galgóczi, B. (2014) selected the Ruhr region in Germany as the research object. By combining the research and survey data on Germany's economic development, it was found that the green transformation practices in the Ruhr region mainly adopted the following measures: establish a specialized regional leading institution to scientifically plan the regional development goals, make efforts to increase financial support and actively introduce advanced technologies, and strengthen the coal industry in terms of intensive transformation to promote optimization and upgrading of traditional industries. Houston has accelerated the implementation of its urban transformation strategy (Klineberg, 2020). Firstly, it has improved the efficiency of resource utilization and intensified efforts to optimize and upgrade traditional industries. Then, it has made full use of national policies to vigorously develop the aerospace industry and the medical technology sector. In addition, it has cultivated emerging industries and increased the proportion of the tertiary industry. Driven by these measures, Houston has broken away from its reliance on resources and achieved the green transformation of a resource-based city.

Based on the Chinese national condition and the official document about resource-exhausted cities, it is crucial to examine the validity of government policy. Using empirical methods and data in resource-exhausted cities, Zhang et al.(2018) made a profound study on the impact of government incentives on transformation and found that the impact depends on whether the authority of the city is the municipal secretary or mayor. Li et al. (2021) explored the policy impact on secondary industries in resource-based cities using data from 282 prefecture-level cities. Research results showed that the supportive policy reduced the share of the secondary sector in gross domestic product. Moreover, this effect was more noticeable in the central and western cities. Sun, Lu, and Cheng (2020) utilized two indicators of GDP per capita and employment to test the effectiveness of the policy in resource-exhausted cities. Some sustainable indicators were utilized in follow-up research, however. Yu et al. (2022) explored the impact of a supportive strategy in resource-exhausted cities from a sustainable development perspective. They utilized the energy efficiency indicators from 284 cities in China and found that the policy has improved the energy efficiency and promoted sustainable development in those cities.

(2) Industrial transformation and upgrading. Many scholars conducted extensive research on industrial transformation at the macro provincial- or city-level. Utilizing city-level data and multiple econometric models, Zhu and Lin (2022) explored the intrinsic relationship between resource dependence and industrial transformation under the circumstances of the market reform in China. The results showed that dependence on natural resources is a major cause of the industrial structure that is dominated by the secondary sector in the process of modernization in China. Li and Guan (2022) conducted an in-depth study around the industrial transformation of the state-owned sector, which revealed that state-owned enterprises could provide a boost for value-enhancement. Lai et al. (2021) evaluated the industrial transformation performance of 30 Chinese provinces and explored the impact of market segmentation on this performance. The empirical regression findings showed an inverted U-shaped correlation between them. Liu et al. (2020) chose 10 resource-

abundant localities in Shanxi province to comprehensively assess their level of sustainable development, not just the economic transformation level, but the coordination level. They suggested that the uppermost priority of the sustainable transformation is the unemployment problem. Also, the government should think highly of the quality of basic education. It might be necessary to introduce the high technology industry and fundamentally raise awareness of sustainable development.

Meanwhile, studies have also been conducted from the micro-enterprise aspect to analyze the industrial transformation. Li and Chen (2022) conducted a series of empirical studies using data from 2009 to 2015 to explore whether green credit policy would affect the operation and production of heavily polluting enterprises. Ultimately, the findings confirmed that this policy has facilitated the diversification and transformation of heavily polluting firms. Luo et al. (2022) studied the industrial development of real enterprises using the TFP of 2064 listed enterprises in China. In summary, it was found that finance technology innovation would facilitate the transformation of these firms, thereby achieving the goal of sustainable development. To verify the actual effect of technological innovation on industrial restructuring and upgrading, Xie and Teo (2022) selected enterprise data from 35 industrial sectors for empirical analysis. The findings suggested that green technological innovation can effectively promote more efficient and cleaner production, but this finding did not hold for the low-value-added industrial sector and the clean sector.

Through the analysis of the existing literature, we find two distinct features of the studies on this topic. (1) Most existing studies at home and abroad use city-level data or county-level data to analyze the industrial transformation of resource-exhausted cities. (2) Among all studies concerning the transformation of resource-based cities, most of them use traditional methods to measure the industrial development. Therefore, corresponding improvements are made in this study to address the shortcomings of the above statements. (1) We will comprehensively discuss the effect of industrial transformation on resource-exhausted cities from both the macro city level and the micro enterprise level. (2) Using enterprise data from 2005-2013, this research chooses the LP method to measure the industrial transformation and upgrading level.

## 2.2 Research hypothesis

Referring to all the above, we suggest that this place-based policy of the State Council may promote the industrial transformation and upgrading both at the city-level and enterprise-level. What's more, industrial upgrading has succeeded in promoting the transition to technology-intensive and high-value chain industries. Thus, this study proposes the following hypotheses:

**Hypothesis 1.** The implementation of the central policy has a positive impact on the optimization of industrial structure (OIS) in resource-exhausted cities.

**Hypothesis 2.** The implementation of central policy could promote the total factor productivity of enterprises in resource-exhausted cities.

**Hypothesis 3.** The implementation of central policy promotes firms' TFP by facilitating the transition of industrial production to technology-intensive and high-value chain industries.

### 3. Models and data

#### 3.1 Empirical models

As an effective tool to assess the experimental effect, the traditional difference-in-difference (DID) model is often used in evaluating the intertemporal effect of public policy. One of the most important advantages of DID model is that it can obtain the genuine effect of policy by modeling and analyzing the data from quasi-natural experiments. According to the official document of the State Council, there are three groups of resource-exhausted cities published in 2008, 2009, and 2011, respectively. Thus, this study uses multi-period DID models to analyze the effect of policy on industrial transformation.

(1) Assess the policy impact on industrial transformation at the city level. This paper first examines the effect of policy on industrial structure at the city level. The multi-period DID model is specified as follows:

$$OIS_{it} = \alpha + \beta \cdot Treat_i \times Post_{it} + \gamma X_{it} + \mu_i + v_t + \varepsilon_{it} \quad [1]$$

where  $OIS_{it}$  is the optimization of the industrial structure of city  $i$  in year  $t$ .  $Treat_i \times Post_{it}$  represents the core explanatory variable that reflects whether city  $i$  is listed as a resource-exhausted city in year  $t$ . This interaction term equals to 1 if city  $i$  is listed as a resource-exhausted city in year  $t$ , otherwise equals to 0. In this model, we are mainly concerned with the magnitude of the coefficient  $\beta_1$  and its significance level.  $\varepsilon_{it}$  is the error term.  $X_{it}$  represents a set of control variables. Drawing from research of Mao et al. (2021), Yuan and Zhu (2018), this study selects fiscal expenditure (FIS), GDP per capita (GDP), foreign direct investment (FDI), environmental regulation (ER), human capital (HC), marketization (MAR), information level (IFM), infrastructure level (IFA) as control variables.  $\mu_i$  and  $v_t$  denote individual and time fixed effects.

(2) Assess the policy impact on industrial transformation from the enterprises level. Based on the empirical analysis above, if the government policy promotes the optimization of city's industrial structure, to a certain extent, it should also promote the transformation of enterprises. To prove this hypothesis, this paper applies the firm data to further explore the impact of the policy on enterprises. Details of the analysis model are as follows:

$$TFP_{ilt} = \alpha_2 + \beta_2 Treat_{il} \times Post_{ilt} + X_{ilt} \gamma_2 + \psi_l + \eta_i + \lambda_t + \varepsilon_{ilt} \quad [2]$$

where  $TFP_{ilt}$  is utilized to evaluate the transformation level of enterprises, which is the total factor productivity of firm  $i$  in city  $l$  in year  $t$  calculated by the LP method.  $Treat_{il} \times Post_{ilt}$  is the core explanatory variable that reflects whether firm  $i$  belongs to a resource-exhausted city in year  $t$ . When city  $l$  where firm  $i$  is located is selected as a resource-exhausted city in year  $t$ , the interaction term equals to 1, otherwise it equals to 0. In this model, we are mainly concerned with the magnitude and significance of the coefficient  $\beta_2$ , as it denotes the actual impact of the policy on firms in resource-exhausted cities.  $X_{ilt}$  represents a set of control variables. With reference to (Li, Yue, and Chen 2016; Wang and Liu 2014; Yu, Sun, and Xuan 2020), this study chooses enterprise scale (ES), enterprise age (AGE), capital density (CD), export share (EX), operating profit margin (PM), financial expenses

(FAN) and so on as control variables.  $\psi_l$ ,  $\eta_i$  and  $v_t$  denote location, individual and time fixed effects.  $\varepsilon_{it}$  is the error term.

### 3.2 Variables and data sources

To analyze the policy impact on industrial transformation from the macro city level, this paper will use city-level data from 284 cities in China from 2004 to 2016. All data in the city-level regression are collected and processed from the China City Statistical Yearbook. The dependent variable is the optimization of industrial structure (OIS), which is measured by the ratio of the tertiary sector to the secondary sector output value. According to the current situation in China, the process of industrial structure upgrading is mainly about the transition to the tertiary industry. What's more, the growth rate of the tertiary industry is usually higher than that of the secondary industry. Thus, compared with using the output value of secondary or tertiary industries, it is more appropriate to use the ratio of these two indicators to measure the changes in industrial structure. A larger OIS value signifies a more rational industrial structure. An increase in OIS value indicates an economic shift towards the service industry and an upgrade of the industrial structure.

To analyze the impact of policy on industrial transformation from the micro-enterprises level, this paper selects firm-level data from a database conducted by the National Bureau of Statistics. This database includes all types and natures of industrial enterprises with detailed information about the identity and address, as well as detailed economic information such as indicators of gross output, employment, profits, and taxes. In addition, to prevent biased estimation, we follow the instruction of Brandt et al. (2012) to process the sample data with a series of treatments to systematically remove the following enterprises: (1) lost key geographical location information, (2) the number of employees less than 8, (3) the operating revenue does not locate in the interval from 0.5 percentage to 99.5 percentage of the distribution, (4) annual sales revenue less than 20 million RMB. The dependent variable in enterprise-level regression is total factor productivity (TFP) of each enterprise.

By combining the previous research literature, we find that the methods of calculating TFP can be classified into three categories. The first category is parametric methods, and the representative ones are stochastic frontier analysis (SFA) and generalized method of moments (GMM). However, the SFA method has to satisfy the assumption about the TFP distribution. This means the final calculation results will be overly dependent on the specific model establishment. Meanwhile, the GMM method needs to ensure that the data period is long enough. The second category is the non-parametric methods, and the representative one is the data envelopment analysis method. One of the biggest drawbacks of this method is that it needs the data to be complete, which means the sample cannot have missing values. It is unrealistic in the data collecting process. The third category is semi-parametric methods, the representative ones are the OP (Olley and Pakes, 1996) method and the LP method (Levinsohn and Petrin, 2003). In this paper, the LP method is used to calculate the TFP of enterprises in China. The main reason for not utilizing the OP method is that it requires the investment of enterprises cannot equal to 0. However, not every enterprise makes a certain amount of investment every year. Therefore, it would generate a large number of missing



values by adopting the OP method. To address this drawback, the LP method makes an improvement by using intermediate inputs as a proxy variable. This improvement makes the data more complete and therefore, obtains a more comprehensive TFP value. At present, the LP method is widely applied to measure the TFP of enterprises (Peng et al. 2021; Tang, Liu, and Wu 2020; Zheng, Wu, and Nepal 2022). Hence, with reference to previous studies, we also adopt the LP method. Table 1 presents basic statistical information about the data used in the empirical analysis. The table includes the variable name, number of observations, mean value, and standard deviation.

**Table 1.** Summary statistics of variables.

City-level	Obs	Mean	Std.dev	Enterprise-level	Obs	Mean	Std.dev
OIS	3692	0.83	0.47	Y	1727013	8.53	1.33
Second	3692	48.94	10.99	K	1727013	6.65	1.70
Tertiary	3692	36.86	8.86	L	1727013	5.08	1.03
FIS	3692	14.05	1.03	M	1727013	8.34	1.36
GDP	3692	3.43	2.91	TFP	1727013	7.29	1.15
FDI	3392	9.74	1.85	ES	1727013	1.99	16.71
ER	3692	11.10	0.98	AGE	1726794	2.01	0.77
HC	3692	1.61	2.17	CD	1727013	2.33	107.85
MAR	3663	16.39	1.40	FAN	1727013	2.14	27.71
IFM	3673	1.05	3.23	EX	1404504	3.43	62.23
IFA	3584	10.02	7.46	PM	1725475	0.045	0.13

## 4. Analysis of empirical results

### 4.1 Baseline regression results

(1) The regression results of the policy impact on industrial transformation at the city level. The Column (2) in Table 2 reports the impact of the supporting policy with full control variables, the coefficient of  $Treat_i \times Post_{it}$  is 0.0645, which is significantly positive at 1% level. This finding denotes that, on average, the resource-exhausted cities have a higher OIS of 0.0645 compared to the non-resource-exhausted cities. To be brief, this result confirms Hypothesis 1, which also sets the stage for further research of enterprises transformation.

(2) The regression results of the policy impact on industrial transformation from the enterprise level. Based on the city-level regression results, we conduct further enterprise-level analysis. The enterprise-level results are presented in Table 3. In theory, the coefficient with all control variables could be more precisely estimate the policy effect. As we can see, the coefficients of  $Treat_i \times Post_{it}$  in Column (2) is significantly positive (0.4076) at 1% level, implying the TFP of enterprises in resource-exhausted cities increases by 0.4076 compared to enterprises in non-resource-exhausted cities. Therefore, this result not only proves Hypothesis 2 but also supports the regression result of city-level analysis.



**Table 2.** Baseline regression results from macro city level.

	(1) OIS	(2) OIS
$Treat_i \times Post_{it}$	0.0210 (0.0218)	0.0645*** (0.0242)
$\mu_i$	Yes	Yes
$\nu_t$	Yes	Yes
$X_{it}$	No	Yes
Observations	3692	3295
$R^2$	0.6912	0.7079

**Note:** The asterisks \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.<sup>2</sup>

**Table 3.** Baseline regression results from micro enterprise level.

	(1) TFP	(2) TFP
$Treat_{it} \times Post_{it}$	0.3894*** (0.0140)	0.4076*** (0.0211)
$\psi_l$	Yes	Yes
$\eta_i$	Yes	Yes
$\lambda_t$	Yes	Yes
$X_{it}$	No	Yes
Observations	1606993	1291280
$R^2$	0.8732	0.8935

**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.

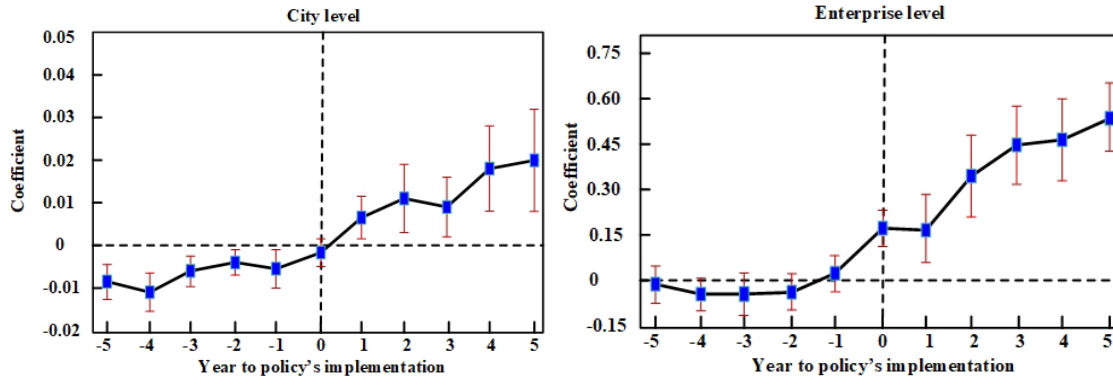
#### 4.2 Parallel trend test

The parallel trend assumption is an important precondition for DID model in empirical paper. In order to utilize the DID model, the target variables in the resource-exhausted cities and non-resource-exhausted cities must satisfy the parallel trend assumption before the policy implementation. We conduct the following regression:

$$TFP_{it} = \alpha_3 + \sum_{j \neq 0, j \geq -3}^5 \theta_j D_{it}^j + X_{it} \gamma_3 + \psi_l + \eta_i + \lambda_t + \varepsilon_{it} \quad [3]$$

where  $D_{it}^j$  is a set of dummy variables. If the city where firm  $i$  located is selected as a resource-exhausted city in year  $t$ ,  $D_{it}^j$  equals to 1, otherwise it equals to 0. The meaning of the remaining variables is the same as Equation 2. In this test, we focus on the coefficient  $\theta_j$ , which reflects the difference in TFP between resource-exhausted cities and non-resource-exhausted cities in the year  $t$  of the policy implementation. The results of the parallel trend test in Figure 1 indicate that the coefficient estimates for each period before the implementation of the support policy are not significant. Therefore, there is no significant difference between firms in treatment group and control group before the policy implementation. Thus, the research sample passed the parallel trend test.

<sup>2</sup> The robustness and heterogeneity tests of city-level baseline regression are not presented in the paper due to the limited space. Interested readers could contact the author for further detailed results.



**Figure 1.** Time trend of the policy implementation (city and enterprises).

## 5. Robustness tests and heterogeneous tests

### 5.1 Robustness tests

#### (1) Alternative measurement of TFP

As mentioned in Section 3.2, there are many other methods to calculate the TFP. To further ensure the robustness of baseline regression, we re-estimate the TFP with OLS and fixed effects (FE) methods. Regression results in this part are displayed in Table 4. The coefficients of  $Treat_i \times Post_{it}$  are still significantly positive. This finding demonstrates the robustness of the primary regression results.

**Table 4.** TFP calculated by the OLS and FE methods.

	(1)	(2)	(3)	(4)
	OLS	OLS	FE	FE
$Treat_{it} \times Post_{it}$	0.4159*** (0.0145)	0.4189*** (0.0217)	0.4173*** (0.0146)	0.4193*** (0.0219)
$\psi_l$	Yes	Yes	Yes	Yes
$\eta_i$	Yes	Yes	Yes	Yes
$\lambda_t$	Yes	Yes	Yes	Yes
$X_{it}$	No	Yes	No	Yes
Observations	1606993	1291288	1606993	1291288
$R^2$	0.8872	0.9058	0.8887	0.9071

**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.

#### (2) Dropping the sample in the year of policy implementation

In the baseline regression model, the treatment group includes enterprises in three groups of resource-exhausted cities in 2008, 2009, and 2011. In order to obtain a more precise difference between treatment and control groups, we drop the sample in these three years to re-estimate the policy effect. The regression results are presented in Column 1 & 2 of Table 5. As we can see, the absolute values of the coefficients are a bit smaller than those of baseline regression. This is because, through dropping the samples from the year of policy implementation, we could obtain a more realistic policy effect. Still, the re-estimation results confirm the robustness of the primary regression.

### (3) Filtering the regression sample

In order to avoid the effect of extreme samples on the regression results, we can truncate the research samples that do not fall in the interval from 1 percent to 95 percent of the distribution. After the truncation process, the estimation results in Column 3 & 4 of Table 5 are still significantly positive at 1% level. This finding confirms the robustness of the regression results of DID model.

**Table 5.** Results of robustness tests.

	(1) TFP	(2) TFP	(3) TFP	(4) TFP
$Treat_{it} \times Post_{it}$	0.3723*** (0.0142)	0.2321*** (0.0182)	0.3880*** (0.0152)	0.4191*** (0.0233)
$\psi_l$	Yes	Yes	Yes	Yes
$\eta_i$	Yes	Yes	Yes	Yes
$\lambda_t$	Yes	Yes	Yes	Yes
$X_{it}$	No	Yes	No	Yes
Observations	1498570	1209291	1345578	1125914
$R^2$	0.8429	0.9110	0.8772	0.8967

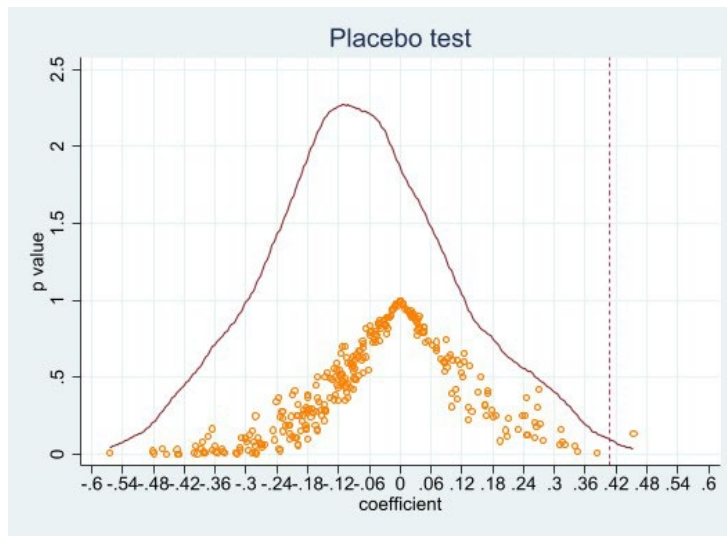
**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.

### (4) Placebo test

In order to avoid some unobservable omitted variables of baseline regression result, we conduct placebo test by randomly selecting different cities 300 times (Cai et al. 2016; Liu and Lu 2015). Firstly, 59 cities are randomly selected from the overall group of cities involved in the research as the placebo treatment group. The placebo treatment group here means that these cities are actually not really affected by the actual policy we are concerned with, but in the process of the test, we will conduct subsequent analyses as if they were affected by the policy. This random selection method can simulate a random, placebo-like treatment state, thus providing a basis for subsequent comparative analyses. Secondly, for the selected 59 cities as the placebo treatment group, statistical models and methods similar to those used in the benchmark regression analysis are applied to calculate the coefficient of the impact of the policy on TFP under this placebo treatment situation.

This coefficient reflects the quantitative manifestation of the virtual policy impact degree under this random setting. Thirdly, in order to make the results more general and stable and avoid the contingency that may be brought about by a single random selection, we repeat the entire process of randomly selecting cities as the placebo treatment group and obtaining the corresponding coefficients 300 times. Each repetition will yield a different coefficient of the impact of the policy on TFP, and at the same time, the corresponding P-value will also be obtained. Finally, the 300 regression coefficients and the corresponding 300 P-values obtained during the 300 repetitions are used to draw a kernel density distribution diagram through professional statistical plotting methods. The kernel density distribution diagram can intuitively show the distribution patterns and central tendencies of these coefficients and P-values. When observing the drawn kernel density distribution diagram, it can be seen that the 300 estimated coefficients present certain distribution rules. Most of them are concentrated around 0, and on the whole, they show the characteristics of a normal distribution. This means that under this random, placebo-like placebo treatment situation, most of the obtained coefficients tend to be close to 0, that is, there is no obvious and systematic impact. Meanwhile, the P-values corresponding to most of the coefficients show that they are not significant,

further indicating that these randomly generated impacts are statistically unreliable and are most likely caused by random fluctuations. Then, we compare the preliminary regression coefficient obtained from the actual benchmark regression analysis with the distribution of these 300 coefficients. As can be seen from the dashed line in Figure 2, the preliminary regression coefficient is located at the high-end tail position of the distribution of the 300 coefficients. In such a placebo test, being in such an extreme position is a low-probability event. In other words, there is a significant difference between the actual benchmark regression coefficient and the coefficient distribution obtained under the random simulation of the placebo situation. Therefore, we have reason to believe that the benchmark regression result is not caused by those unobservable and random omitted variables, but truly reflects the real impact of the studied policy on TFP.



**Figure 2.** The placebo test.

#### (5) Applying the balanced panel data

According to the data cleaning process in Section 3.2, we finally obtained unbalanced panel data of 1.73 million observations. If there were some inconsistencies in the imbalanced panel data, the primary estimation would be biased. Therefore, this part chooses to apply the balanced panel data for noise reduction and then verify the robustness of the baseline estimation. All of the coefficients in Table 6 are still positive at 1% significance level, which suggests that the policy does promote enterprises' TFP in resource-exhausted cities.

**Table 6.** Selecting balanced panel data.

	(1) TFP	(2) TFP
$Treat_{it} \times Post_{it}$	0.2415*** (0.0138)	0.1982*** (0.0152)
$\psi_l$	Yes	Yes
$\eta_i$	Yes	Yes
$\lambda_t$	Yes	Yes
$X_{it}$	No	Yes
Observations	563635	502160
$R^2$	0.8589	0.8758

**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.

### 5.2 Heterogeneous tests

In the following analysis, we further examine the heterogeneous effect of the central supporting policy on enterprises across regions, industry categories, and ownership types. Thereby, we could comprehensively understand the specific influence mechanism of the policy.

The first dimension compares the western regions and the non-western regions. As we could see in Column 1 and 2 of Table 7, the policy effects are all significantly positive. However, the estimated coefficients in non-western regions are larger and more significant than in western regions. According to previous literature, superior geography would create a better business environment, such as stricter intellectual property laws and more sufficient public finances (Acemogl et al., 2012; Rodrik, Subramanian et al., 2004). As a result, producers are more likely to respond to government policy in a relatively superior business environment. Our results are consistent with that previous research, which also validates the baseline regression results.

The second dimension compares the different industry sectors. The industry sectors include the mining industry, the manufacturing industry, and the electricity, heat, and gas industry. The production of these industries all involves resource consumption. According to Columns 3 and 4 of Table 7, we can see that all coefficients are still significantly positive. However, the policy has a greater impact on TFP of the manufacturing industry. One possible reason is that the transformation of the manufacturing industry is more easily successful than the mining industry and the electricity, heat, and gas industry. Because the production of these two industries is so dependent on natural resources, transformation and upgrading are still hard for them (J. Li et al. 2022).

The last dimension compares the ownership types: state-owned enterprises, private enterprises, and foreign companies. The impact of the three columns in Table 8 is different. The private and foreign enterprises react much more greatly than state-owned enterprises and the coefficients of these two types of enterprise are positive. However, the coefficient of state-owned company is small and negative. Institutional differences may be responsible for this regression result (Brandt and Li, 2003; Kornai, 2001). During the production start-up stage, state-owned enterprises usually have easier access to bank loans. This is because state-owned enterprises often have a special status and a close connection with the government, which makes banks and other financial institutions more inclined to them when granting loans. Meanwhile, the government often uses financial institutions to support state-owned enterprises, taking financial institutions as a means to enable state-owned enterprises to obtain the financial assistance needed in the production process more conveniently. However, this relatively easy access to funds has brought about some negative impacts. Due to the relatively easy access to funds, state-owned enterprises may lack sufficient motivation to achieve efficient production. Unlike private enterprises and foreign-funded enterprises, they do not face greater financial pressure and thus do not need to continuously optimize the production process and improve production efficiency to ensure the survival and development of the enterprises. Over time, this lack of motivation for efficient production has ultimately led to the failure of industrial transformation and upgrading, making it difficult for state-owned enterprises to achieve ideal results in aspects such as industrial structure adjustment and moving towards industrial links with higher added value. Consequently, they have gradually shown a different situation from private enterprises and foreign-funded enterprises in overall market competition and

industry development, which also reasonably explains the differences in the regression results presented in Table 8 mentioned earlier. In conclusion, the differences in ownership types, through institutional differences and different performances in aspects such as production and credit, jointly result in different impact results and reaction degrees when enterprises face the same research factors.

**Table 7.** Heterogeneous treatment effect across regions and industries.

	(1) West regions	(2) Non-west regions	(3) Manufacturing industry	(4) Other industry
$Treat_{it} \times Post_{it}$	0.1506** (0.0691)	0.4229*** (0.0221)	0.4299*** (0.0235)	0.1361*** (0.0486)
$\psi_l$	Yes	Yes	Yes	Yes
$\eta_i$	Yes	Yes	Yes	Yes
$\lambda_t$	Yes	Yes	Yes	Yes
$X_{it}$	Yes	Yes	Yes	Yes
Observations	100544	1190733	1218331	72137
$R^2$	0.9187	0.8909	0.8916	0.9237

**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.

**Table 8.** Heterogeneous treatment effect across ownership types.

	(1) State-owned	(2) private	(3) foreign
$Treat_{it} \times Post_{it}$	-0.0382 (0.0387)	0.4344*** (0.0263)	0.3341** (0.0744)
$\psi_l$	Yes	Yes	Yes
$\eta_i$	Yes	Yes	Yes
$\lambda_t$	Yes	Yes	Yes
$X_{it}$	Yes	Yes	Yes
Observations	74846	691874	198754
$R^2$	0.9624	0.8958	0.9193

**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are presented in parentheses.

## 6. Mechanism analysis

The supportive policy in resource-exhausted cities is promulgated to increase employment, eliminate poverty and maintain socio-economic stability. Industrial transformation is the only way to achieve these goals. Industrial transformation and upgrading can be summarized in three evolutionary procedures. First, transforming from the primary sector to the tertiary sector industry; Second, transforming from a resource-intensive and labor-intensive industry to a technology-intensive industry; Third, transforming from low-value chain to high-value chain. In this section, we conduct two tests to analyze the transformation mechanism channel from the perspective of average wages.

We expect the implementation of the central policy to lead to a shift in industrial production to technology-intensive and high-value chain industries. This transition would be reflected in more high-skilled labor and less low-skilled labor in the market. However, we cannot obtain the data of employment by skill level of enterprises. To solve this problem, we calculate the indicator of average wages ( $AW_{it}$ ) by dividing the total cost of employment by the total number of employees. Here we

utilize an important assumption that wages of high-skilled labor are higher than wages of low-skilled labor (S. Li, Wang, and Zhang 2022). In a relatively well-developed labor market, wage levels are often determined by the supply and demand relationship of labor. Generally speaking, high-skilled labor forces, with their relatively scarce professional knowledge, complex skills and strong problem-solving abilities, etc., can create higher value for enterprises. Therefore, under market competition, enterprises are willing to pay higher wages to this type of labor to attract and retain them. In addition, considering China's national conditions and the availability of data, it is quite appropriate to select the average wage to represent the level of labor skills.

The first test is a difference-in-differences (DDD) estimation model. Based on lessons from Cai et al. (2016), we introduce a mechanism variable and construct an interaction term of  $Treat_{it} \times Post_{it} \times AW_{it}$  to validate the mechanism analysis from an average wage perspective. The DDD model specification is:

$$TFP_{it} = \alpha_4 + \beta_4 Treat_{it} \times Post_{it} \times AW_{it} + X_{it}\gamma_4 + \psi_l + \eta_i + \lambda_t + \varepsilon_{it} \quad [4]$$

where  $AW_{it}$  is the average wage of each enterprise. All the other variables in Equation 4 remain consistent with those in the baseline regression. In this mechanism analysis section, our major concern is the coefficient  $\beta_4$ . The mechanism regression results are presented in Columns (1) and (2) in Table 9.

The second test is a two-stage mediating effects model. Baron and Kenny (1986) provided a useful method for us; we constructed the following model to empirically identify the mechanism analysis from an average wage perspective. The two-stage mediating effects model specification is:

$$AW_{it} = \alpha_5 + \beta_5 Treat_{it} \times Post_{it} + X_{it}\gamma_5 + \psi_l + \eta_i + \lambda_t + \varepsilon_{it} \quad [5]$$

$$TFP_{it} = \alpha_6 + \beta_6 Treat_{it} \times Post_{it} + \tau AW_{it} + X_{it}\gamma_6 + \psi_l + \eta_i + \lambda_t + \varepsilon_{it} \quad [6]$$

where mediating variable remains average wage of enterprises ( $AW_{it}$ ). All the other variables in Equation 5 and 6 remain consistent with those in the baseline regression. In this part, our major concern is  $\beta_5$  and  $\beta_6$ . The results of mediating effects model are presented in Columns (3) and (4) in Table 9.

**Table 9.** Results for mechanism analysis.

	DDD model		Mediating effect model	
	(1)	(2)	(3)	(4)
	$TFP_{it}$	$TFP_{it}$	$AW_{it}$	$TFP_{it}$
$Treat_{it} \times Post_{it}$	0.0328*** (0.0012)	0.0334*** (0.0018)	-	-
$Treat_{it} \times Post_{it} \times AW_{it}$	-	-	0.0796*** (0.0256)	0.3989*** (0.0216)
$AW_{it}$	-	-	-	0.1370*** (0.0017)
$\psi_l$	Yes	Yes	Yes	Yes
$\eta_i$	Yes	Yes	Yes	Yes
$\lambda_t$	Yes	Yes	Yes	Yes
$X_{it}$	No	Yes	Yes	Yes
Observations	1559540	1270221	1270221	1270221
$R^2$	0.8750	0.8942	0.8125	0.8974

**Note:** \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance levels, respectively. Detailed standard errors are



presented in parentheses.

According to Columns (1) and (2) of Table 9, the coefficients of the triple difference term are the main areas of concern. It is clear that the coefficients are positive and significant whether the regression involves control variables or not. This result suggests that supportive policies promote an increase in the highly skilled labor force. Based on the previous hypothesis, we can infer that central policy promotes the shift of industrial production to technology-intensive and high-value chain industries. What's more, the coefficients in Columns (3) and (4) of Table 9 provide further evidence of the mediating effect of this mechanism channel. The findings denote that the central policy has a positive effect on increasing the wages of highly skilled labor. Moreover, the central policy promotes enterprises' TFP by increasing the wages of high-skilled labor. The findings in the mechanism analysis are also consistent with previous studies (Larrain 2015).

In summary, we may conclude that the policy increases enterprises' TFP by facilitating the transition of industrial production to technology-intensive and high-value chain industries, as reflected in the increase of average wages. All the findings in this section are compatible with Hypothesis 3.

## 7. Conclusion and implications

Since the 18<sup>th</sup> CPC National Congress, China has regarded ecological civilization as an important content of the construction of a harmonious society. Analyzing the development of resource-exhausted cities is not only promoting transformation of these cities, but also offering experiences for transformation of other cities in China. Therefore, our research applies DID model to examine the effects of transformation and upgrading of resource-exhausted cities from both city-level and enterprise-level. Further robustness tests and heterogeneous tests verified the baseline regression results.

According to the research above, the main conclusions are summarized as follows: First, the policy has substantially increased the TFP of enterprises located in resource-exhausted cities. Specifically, enterprises located in resource-exhausted cities have an increased TFP of 0.4076 compared with enterprises located in non-resource-exhausted cities. This result is also validated through follow-up robustness and heterogeneous tests. Second, the impact of the policy is different among three types of enterprises. According to the heterogeneous test in Section 5.2, the policy did not favor the state-owned enterprises because they lack the motivation of transformation due to their institutional advantages. Third, based on the results of the mechanism analysis, we may conclude that the policy promotes firms' TFP by facilitating the transition of industrial production to technology-intensive and high-value chain industries. Finally, in view of the above-mentioned findings, we wish to draw the following implications.

(1) Enterprises of different ownership types, different scales, and in different industries have diverse problems and advantages in the process of transformation. Therefore, policy formulation needs to fully consider these differences and formulate exclusive support policies for different types of enterprises. For example, policies for state-owned enterprises can be designed to help break institutional barriers, stimulate internal transformation motivation, and provide policy support for

private enterprises in aspects such as more convenient financing channels and market access opportunities.

(2) The economic development levels, industrial foundations, and resource endowments in different regions vary. For economically developed regions, policies can focus on guiding enterprises to transform towards higher value-added fields such as high-end manufacturing and high-tech industries, and encourage the research and development and innovative application of cutting-edge technologies. In resource-based regions, it is necessary to formulate policies to promote the transformation of traditional resource industries towards green and sustainable industries, deep processing, and related emerging industries around the needs of the transformation of resource-exhausted cities. For example, offer tax incentives and special subsidies to enterprises in resource-exhausted cities to help them break away from their dependence on a single resource and achieve industrial upgrading.

(3) The government can set up special transformation funds and provide financial subsidies to enterprises that are actively carrying out transformation according to a certain proportion of their transformation investments, which can be used for aspects such as technological research and development, equipment renewal, and personnel training. Meanwhile, by reducing relevant taxes and fees of enterprises, such as lowering enterprise income tax and value-added tax, the cost pressure on enterprises during the transformation period can be alleviated, enabling enterprises to invest more funds into transformation and upgrading.

(4) Formulate attractive talent introduction policies. For example, provide high-end talents with favorable treatments such as housing subsidies, preferential policies for children's education, and start-up funds for scientific research to attract talents with advanced technologies and management experience to work in transforming enterprises and make up for the shortage of professional talents in the process of enterprise transformation. Support enterprises in carrying out cooperation in running schools, targeted training, and other projects with universities and vocational colleges. According to the actual talent needs of enterprise transformation, jointly formulate training programs to cultivate skilled and innovative talents that meet the requirements of enterprise technological upgrading and business expansion. Meanwhile, the government can fund free skill training programs for enterprise employees to improve the overall quality of enterprise employees and lay a solid talent foundation for enterprise transformation.

There is still much room for further study. This study only covers the short-term data from 2008 to 2013. When long-term data is available, further studies can follow up and analyze the long-term effect of the policy.

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