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Wang, Jian-xiu and Hou, Dan-dan and Zhong, Shun-chang and You, Yun-tian

14 April 2025

Induced-agglomeration policy, firm productivity and survival: evidence from China

Jian-xiu Wang[1]✉ Dan-dan Hou[2] Shun-chang Zhong[3] Yun-tian You[1]

Abstract

Research conducted worldwide has established that industrial agglomeration can improve firm productivity, regardless of policy and institutional factors. In this study, we utilize firm-level data from the Chinese Industrial Enterprises Database (CIED) for the period of 1998-2014 to analyze the relationship between induced-agglomeration policy and the productivity of firms operating within industrial parks while considering productivity and regional heterogeneities. To ensure the reliability of our results, we adopt various identification strategies that produce consistent outcomes. Additionally, we examine the impact of induced-agglomeration policy on firm survival in industrial parks by utilizing a Cloglog survival model. Our findings indicate that induced-agglomeration policy has a negative effect on the productivity of firms operating within industrial parks, with the negative effects diminishing as TFP increases and being stronger in less developed areas. We also find that induced-agglomeration policy can effectively enhance the lifespan of firms, particularly in less developed regions. We then point out policy optimization and other future research topics.

Keywords induced-agglomeration policy • productivity • survival • China

JEL Classification P21 • P25 • P27

1 Introduction

Industrial parks are crucial for improving resource allocation and promoting incremental economic development in China. The healthy development of industrial parks is closely linked to the construction of China's modern economic system and the strategy of deepening supply-side structural reform. However, with the continuous expansion in the number and scale of industrial parks in China, many parks face practical issues such as a lack of industrial cluster effects, low-end industrial

[1]School of Management Science and Engineering, Shanxi University of Finance and Economics, Taiyuan, China. [2]Department of economic management, Jinzhong University, Jinzhong, China. [3]Institute of Resource-based Economic Transformation Development, Shanxi University of Finance and Economics, Taiyuan, China.
✉email:wjx004@sina.com

development, industrial homogeneity (Mao, Yang and Han, 2019), and idle resources. These challenges have reduced the efficiency of land, capital, and talent utilization, hindered the optimal allocation of resources, and affected the healthy and sustainable development of regional economies. Addressing the development problems of industrial parks is a key measure for the Chinese government to accelerate economic and industrial structural adjustments and foster coordinated development of market elements. It is also the main battleground for achieving China's industrial revitalization strategy. Firms are the micro-subjects of industrial park development. Exploring the development and survival capabilities of firms within industrial parks is the premise and foundation for solving these problems.

In China, an industrial park is an area planned by the state or local government to gather a number of industrial firms. Since the establishment of the Shekou Industrial Zone in 1979, China has been implementing various types of industrial parks in different areas, which have played a crucial role in making China a prominent global economic center. The implementation of industrial parks began with Shekou and expanded to other cities such as Zhuhai, Shantou, Xiamen, and 14 other coastal port cities in the early 1980s. China successively opened the Yangtze River Delta and the Xia-Zhang-Quan Delta, followed by Hainan Province in 1988 and Shanghai in 1990. Since 1991, the establishment of development parks has gradually shifted to inland regions. From 2003 to 2006, China carried out the cleaning and reorganization of industrial parks. The construction of industrial parks during those three years was relatively standardized, but in 2006, China experienced another peak of industrial park construction. Additionally, a large number of industrial parks were built in central and western China to balance regional development. The government's crucial role in promoting industrial agglomeration is evident through the development of industrial parks in China.

Numerous studies have demonstrated that spatial clustering of firms results in increased productivity levels for those firms, largely due to the positive externalities that arise from this clustering. These externalities can take many forms, such as the availability of concentrated labor markets, the potential for shared suppliers, and the knowledge spillovers that result from the so-called "agglomeration effects" (Smith, 1976; Marshall, 1961; Duranton and Puga, 2004; Saito and Gopinath,.2009, Combes et al.,2012; Greenstone, Hornbeck and Moretti, 2010). Another view is that larger markets attract more firms, leading to increased competition and the exit of less productive firms from the market (Melitz, 2003; Melitz and Ottaviano,2008). This suggests that in larger areas, the higher average productivity of firms and workers could instead result from the "Darwinian selection of firms." The literature reviewed fails to fully account for the impact of political institutions, which are a crucial determinant of firm productivity. China's institutional background differs from that of Western developed countries, with the government playing a more important role in the state-led "socialist market economy" (Naughton,2010). The development of industrial parks in China is affected by specific institutions, which serve as an important factor influencing the functionality of spatial agglomeration logic, indicating that the significance of industry clusters has surpassed its original meaning.

The government can promote industrial development through means such as land policies, industrial policies, and tax policies, which are relatively less important in the New Economic Geography. However, when examining the potential impact of industrial agglomeration on firm productivity in China, it is imperative to consider the role of government intervention as a crucial variable. At the same time, economic data plays a critical role in evaluating officials in China, often resulting in local officials prioritizing industrial construction projects regardless of the cost. Therefore, in the construction of industrial parks in China, various policy inducements from the government are very important. In this paper, we refer to the policy aimed at encouraging the agglomeration of firms and industries in a specific geographic location through various incentives and measures as "induced-agglomeration policy."

The goal of this paper is to investigate whether induced-agglomeration policy has improved firm productivity and survival in China. To achieve this, our initial work is to analyze the distributional characteristics of firm productivity inside and outside industrial parks in China. Based on this, we conduct further research to explore the impact of induced-agglomeration policy on firm productivity. We use firm-level data from the Chinese Industrial Enterprises Database (CIED) for the period of 1998-2014 to explore the impact of induced-agglomeration policy on firm productivity. To provide a more comprehensive analysis of causal mechanisms, we employ multiple identification strategies, all of which produce consistent results. Firstly, we construct two-way fixed effects models that control for a detailed set of fixed effects and employ a quantile approach to trace productivity differences. Secondly, we present visual evidence of the dynamic effects of induced-agglomeration policy by conducting an event study analysis and investigate the longer-term dynamic effects using distributed lag models. We further examine the impact of induced-agglomeration policy on firm survival by using a discrete-time complementary log-log (Cloglog) survival model.

The findings of this paper can be summarized as follows: The distribution curve of firm productivity in Chinese industrial parks does not exhibit left truncation, indicating that the firm selection effect does not occur. This implies that industrial agglomeration parks are not solely accessible to high-productivity firms. The theoretical analysis and empirical results suggest that induced-agglomeration policy has an adverse impact on firm productivity. Even though the distribution curve has shifted to the right compared with the distribution outside the industrial parks, indicating that agglomeration effects have played a role, low-productivity firms that enter industrial parks through induced-agglomeration policy can still restrain the productivity improvement of firms in industrial parks. The magnitude of the negative effect diminishes as firms' total factor productivity (TFP) increases and is more pronounced in less developed regions. In addition, our findings also reveal that induced-agglomeration policy has a positive impact on firm survival, particularly in less developed regions.

The study offers several notable contributions. Firstly, it explores the impact of policy and institutional factors on firm productivity in Chinese industrial parks, providing a more comprehensive understanding of firm productivity features in industrial agglomeration beyond "firm selection" and "agglomeration effects" typically emphasized in existing free-market-based theories. Secondly, we adopt various identification strategies that produce consistent outcomes, making our estimation more convincing. Thirdly, although the induced-agglomeration policy does not improve the productivity of firms in industrial parks, it does prolong their survival, which could have a negative impact on the development of industrial parks and lead to a “policy contradiction”. Finally, our findings establish a scientific foundation for comprehending the productivity and survival traits of firms in industrial parks in China, while also offering guidance for other nations with comparable institutional structures.

This paper is structured as follows: Section 2 presents the theoretical analysis and research hypotheses. Section 3 provides a detailed account of the data used in the study, including key summary statistics. In Section 4, we present the empirical research methods employed, as well as the results of the study. Subsequently, Section 5 is dedicated to discussion and limitations, while Section 6 offers concluding remarks.

2 Theoretical analysis and hypotheses

“Firm selection” and “agglomeration economies” are the two main explanations that have been identified to illustrate the productivity advantages for firms located in agglomeration areas (Duranton and Puga, 2004; Melitz, 2003; Melitz and Ottaviano, 2008, Henderson, 1974; Sveikauskas, 1975; Rosenthal and Strange, 2004; Head and Mayer, 2004; Kline and Moretti,2014). Given that policies and institutions also play a significant role in shaping the productivity of firms located within industrial agglomerations, this article investigates the productivity levels of firms in Chinese industrial parks through the lens of the “induced-agglomeration policy”.

To do so, we expand upon the theoretical model of Hsieh and Klenow (2009) by incorporating the distinctive national conditions of China (Hsieh and Klenow, 2009). We introduce the factor price effect[①] of biased technological change discussed by Acemoglu (2002) into the HK model (Acemoglu, 2002). In China, the government primarily promotes the growth of industrial parks by providing financial subsidies and tax breaks, with the explicit goal of rapidly boosting capital accumulation and

① The factor price effect refers to the discount in factor prices that firms in industrial parks receive due to cost advantages provided by the government before the transaction, tax exemptions during the transaction, and tax refunds after the transaction, resulting in the actual cost of factors paid by the firms being lower than the market price (Lu, Liu and Liu, 2021).

expanding production capabilities in firms. This approach helps to rapidly promote industrial agglomeration and economic growth. The government's reliance on these policies, rather than solely on market mechanisms, is due to the prolonged cycles and high uncertainty associated with market-driven processes. Measures like discounts on utilities (electricity, water, natural gas, and heating), tax rebates, innovation funds, and reduced or preferential land transfer fees directly encourage firm clustering, reduce operational costs, and boost cash flow. Therefore, our model assumes that such policies lead to a decrease in capital costs. While these incentives do impact product prices, and technological levels may improve due to knowledge spillover, these mechanisms within industrial parks do not manifest as immediately or powerfully as government policy effects. Reflecting on this, we represent the factor price effect in the form of an increasing function of the intensity of induced-agglomeration policy.

We assume there are *s* industrial parks in an economy, where each park comprises *i* firms. The production function for each firm is given by a Cobb-Douglas function with constant returns to scale, which incorporates firm TFP, capital, and labor:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{1}$$

Here, Y refers to the output, A refers to firm TFP, α represents output elasticity of capital, and 1-α represents output elasticity of labor.

Profits for firms in industrial parks are given by

$$\pi_{si} = PY_{si} - WL_{si} - (1 - \tau_{k_{si}}) RK_{si}\,, 0 < \tau_{k_{si}} < 1 \tag{2}$$

Where P represents the price of the final product. W and R are the prices of labor and capital without distortions, respectively. Due to the fact that the government provides a range of explicit factor price subsidies to firms located in industrial parks, such as tax exemptions, tax refunds, and fiscal subsidies, the actual capital price faced by firms is reduced to $(1-\tau_{k_{si}})R$, where $\tau_{k_{si}}$represents the unit capital price reduction obtained by firm i due to policy-induced incentives. The more robust the induced agglomeration policy, the greater the reduction in the unit capital cost for the firm. Therefore, it can be concluded that there is a positive relationship between the factor price reduction $\tau_{k_{si}}$ and the intensity of induced-agglomeration policy G_{si}, that is, $\tau_{k_{si}} \propto G_{si}$. Maximizing profits allows us to calculate the prices of labor and capital without distortions:

$$W = \frac{(1-\alpha_s)PY_{si}}{L_{si}} \tag{3}$$

$$R = \frac{\alpha_s PY_{si}}{K_{si}\left(1-\tau_{k_{si}}\right)} \tag{4}$$

The equilibrium demand ratio between the quantity of capital and labor can be further obtained as:

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s} \cdot \frac{W}{\left(1-\tau_{k_{si}}\right)R} \tag{5}$$

Next, let us substitute (5) into (3) or (4). This gives the function of P, the price of the final product:

$$P = \left(\frac{R}{\alpha_s}\right)^{\alpha_s} \left(\frac{W}{1-\alpha_s}\right)^{1-\alpha_s} \frac{\left(1-\tau_{k_{si}}\right)^{\alpha_s}}{A_{si}} \tag{6}$$

The marginal revenue product of labor is：

$$MRPL_{si} = (1-\alpha_s)\frac{PY_{si}}{L_{si}} = W \tag{7}$$

And the marginal revenue product of capital is:

$$MRPK_{si} = \alpha_s \frac{PY_{si}}{K_{si}} = \left(1-\tau_{k_{si}}\right)R \tag{8}$$

We define “revenue productivity” as follows:

$$TFP_{si} \triangleq A_{si} \tag{9}$$

$$TFPR_{si} \triangleq PA_{si} = \frac{PY_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{10}$$

Using the geometric mean of the marginal products of capital and labor, the relationship between $TFPR$ and $\tau_{k_{si}}$ is expressed:

$$\begin{aligned} TFPR_{si} &= \left(\frac{MRPK_{si}}{\alpha_s}\right)^{\alpha_s} \left(\frac{MRPL_{si}}{1-\alpha_s}\right)^{1-\alpha_s} \\ &= \left(\frac{R}{\alpha_s}\right)^{\alpha_s} \left(\frac{W}{1-\alpha_s}\right)^{1-\alpha_s} \left(1-\tau_{k_{si}}\right)^{\alpha_s} \end{aligned} \tag{11}$$

Formula (11) shows that the "revenue productivity" $TFPR$ is inversely proportional to both the capital price reduction $\tau_{k_{si}}$obtained by the firm. As $\tau_{k_{si}} \propto G_{si}$, the following equation holds true.

$$TFP_{si} \propto TFPR_{si} \propto \frac{1}{\tau_{k_{si}}} \propto \frac{1}{G_{si}} \tag{12}$$

Formulas (11) and (12) indicate that: (1) Induced-agglomeration policy accelerates the decline in firm productivity by adjusting capital factors. (2) The intensity of induced-agglomeration policy has an inverse relationship with TFP, such that TFP decreases as the intensity of induced-agglomeration policy increases.

Through theoretical model deduction, it becomes evident that the induced-agglomeration policy undermines firm productivity. This is because government subsidy measures may lead to imbalances in resource allocation (Acemoglu et al.,2010), distortion in market competition (Aghion and Howitt, 1992), and a weakening of firm innovation drive (Aghion et al.,2005). With various subsidy and preferential policies in place, firms are more inclined to rely on subsidies rather than enhancing efficiency and innovation to improve productivity. This dependency also results in firms lacking competitiveness and innovation spirit (Branstetter, Fisman and Foley, 2006). Additionally, subsidized firms gain unfair competitive advantages in the market, thereby diminishing the productivity of other firms as they must face cost pressures compared to their competitors. Moreover, government intervention may distort market signals, making it difficult for firms to accurately assess market demand and competitive conditions. This could lead to production mismatches with market demand, further reducing productivity.

Furthermore, the degree to which the induced-agglomeration policy negatively affects firm TFP will vary across regions. In the early 1990s, the Chinese government started promoting regional coordinated development to facilitate overall economic growth and balance economic development across different regions. Since 2003-2004, substantial fiscal transfer payments have been implemented in the underdeveloped regions, in order to support their development. These areas have also been given priority in the allocation of construction land indicators, while land supply has been restricted in the developed regions. In addition, there are incentives in place for underdeveloped regions to boost their local GDP. As a result, there has been a significant influx of resources into these regions, while resources in the developed regions are comparatively limited (Lu and Xiang, 2014). Consequently, the intensity of induced-agglomeration policy in underdeveloped regions surpasses that of developed regions, denoted as G_{su}>G_{sd}. G_{su} refers to the intensity of induced-agglomeration policy in underdeveloped regions, while G_{sd} refers to the same in developed regions.

These lead to two following hypotheses：

Hypothesis 1. Induced-agglomeration policy in China has a negative impact on the productivity of firms within industrial parks.

Hypothesis 2. The negative effects of induced-agglomeration policy on the productivity of firms within industrial parks are more pronounced in underdeveloped regions compared to developed regions.

Our next step is to analyze the impact of induced-agglomeration policy on the survival of firms located within industrial parks. To begin with, it is apparent that the Chinese government has extensively intervened in the development of firms and the allocation of resources through non-market mechanisms (Deng, 2016). Policy tools, such as subsidies, tax breaks, and other preferential treatments, have been used to adjust the size of "policy rent" and modify the cost-benefit ratio of firms. Because industrial parks play a crucial role in promoting local economies and stabilizing employment, firms located within these parks can benefit from more government support and a competitive advantage, which contributes to their long-term viability. Meanwhile, due to China's coordination strategy's strong focus on underdeveloped regions, the induced-agglomeration policy has a more pronounced effect on the viability of firms located within industrial parks in these regions.

Secondly, the imperfect bankruptcy judicial system for firms creates significant obstacles for inefficient firms trying to exit the market (Wang and Liu, 2018). If the design of the bankruptcy system is improved to reduce obstacles to firm restructuring, inefficient firms would have a higher probability of exiting the market. This would lead to a faster allocation of capital to firms with higher productivity, ultimately promoting economic efficiency. However, due to existing institutional roots, inefficient firms in industrial parks can continue to survive for an extended period under the protection of the government's preferential policies. Moreover, local governments have a tendency to favor incumbent firms while easing the elimination of low-productivity ones to maintain GDP growth, employment stability, and inter-regional capital competition (Huang and Chen, 2017).

Based on the aforementioned factors, we propose the following hypothesis:

Hypothesis 3. Induced-agglomeration policy is positively associated with the duration of firms operating in industrial parks, with stronger positive effects observed in less developed areas compared to developed areas in China.

3 Data and variables

3.1 The data

For this study, we utilize firm-level data from the Chinese Industrial Enterprises Database (CIED) collected by China's National Bureau of Statistics (CNBS) during the period of 1998-2014②. This database contains comprehensive information, such as firm code, number of employees, ownership, location, and primary financial indicators, for all state-holding and non-state-holding industrial firms with annual operating income exceeding 5 million RMB prior to 2011 and exceeding 20 million RMB from 2011 onwards.

Based on the "legal person code", "legal person name", "province name", "city name", "district name", and "industry code", we match an unbalanced panel dataset covering the years 1998-2014 (excluding 2010). Following the methodology used by Chen et al. (2015) and Li and Wu (2018) (Chen, Lu and Xiang, 2015; Li and Wu, 2018), we identify firms located in industrial zones by searching for certain keywords in the firm's address information.These keywords are derived from the Catalogue of China Development Audit Announcement (2018 edition) and include terms such as '*kaifa*' (development), '*gaoxin*' (high-tech), '*jingkai*' (economic development zone), '*jingji*'

② Although the EPS database has updated the data for industrial enterprises above designated size to 2015, it was not utilized in this study due to issues such as confusion in industrial enterprise identification codes and the lack of disclosure of legal entity codes and names, which make accurate sample matching difficult. As a result, this study's sample observation period is limited to 1998-2014.

(economy), '*yuanqu*' (zone), '*baoshui*' (bonded area), '*bianjing*' (border-area-located), '*kejiyuan*' (science and technology park), '*chanyeyuan*' (industrial zone), '*huojuyuan*' (torch high-tech park), '*huojuq*u' (torch high-tech zone), '*gongyeyuan*' (industrial park), '*chuangyeyuan*' (pioneer park), '*gongyequ*' (industrial area), '*touziqu*' (investment zone), '*gongyexiaoqu*' (industrial district), and '*chukoujiagong*' (export processing zone).

To ensure the cleanliness of the sample and eliminate outliers, we exclude the following observations from the original dataset:

• observations with missing or negative values for one of the following variables: (i) gross output value, (ii) industrial value added, (iii) fixed-assets, (iv) intermediate input[28];

• observations with less than eight employees (Brandt et al., 2012);

• misclassified observations meeting any of the following conditions: (i) total assets are clearly smaller than current assets, (ii) total assets are clearly smaller than fixed assets, (iii) accumulated depreciation is lower than current depreciation (Cai and Liu, 2009);

• observations in the year 2010 for the following reason: the core indicators used to measure TFP are not available in the data. Only three indicators, namely, final number of employees, annual operating income, and sales revenue are available (Nie et al., 2016);

• individuals with data available for only one-year.

Following the aforementioned procedure, our dataset consists of 667,169 observations from 155,386 firms. The proportion of firms in the industrial park by year is shown in Table 1.

TABLE 1 The number and proportion of firms in industrial parks

Variables	1998	1999	2000	2001	2002	2003	2004	2005
Total number of firms	116,858	139,484	135,932	147,084	165,217	178,831	173,792	192,321
Total number of firms in industrial parks	8,326	10,899	12,272	14,934	18,289	21,016	35,381	38,211
The proportion of firms in industrial parks to total number of firms (%)	7.12	7.81	9.03	10.15	11.07	11.75	20.36	19.87
Variables	2006	2007	2008	2009	2011	2012	2013	2014
Total number of firms	223,094	255,378	366,059	306,418	282,012	282,872	293,288	157,157

Total number of firms in industrial parks	40,317	44,494	79,800	66,910	68,922	73,157	81,736	52,505
The proportion of firms in industrial parks to total number of firms (%)	18.07	17.42	21.80	21.84	24.44	25.86	27.87	33.41

In order to investigate the relationship between induced-agglomeration policy and firm survival, we consider a firm to have "failed" if it appeared in the CIED in year t but not in any subsequent year from t+1 to 2014, following the methodology of Disney et al. (2003) (Disney, Haskel and Heden, 2003). To address issues related to data censoring and truncation, we exclude the following types of observations from the above dataset:

• individuals with left-censored data. The dataset in this paper covers the period from 1998 to 2014, so firms founded before 1998 have an unknown starting date, resulting in left-censored data. Estimating models on left-censored data can introduce biases in the estimated hazard rate since the true elapsed duration of left-censored spells is unknown and under-recorded (Hess and Persson, 2012). Therefore, we only keep firms founded after 1998.

• individuals with interval-truncated data (Besedeš and Prusa, 2006). Some individual observations in the CIED are not continuous due to factors such as changes in statistical caliber or operating conditions, resulting in the "interval truncation" of the data. For example, some firms were reopened, or some firms were in the CIED database again because their income was above the scale again. For instance, some firms may have temporarily ceased operations and then resumed them later, resulting in a gap in their observations in the CIED. In other cases, firms may have left the CIED database due to falling below a certain income threshold, only to re-enter the database again later when their income exceeded the threshold. To address this issue, we only include individuals with continuous observations in our analysis.

• individuals that are still operational but have withdrawn from industrial parks after several continuous years. Although these individuals are still operational, they are no longer located in an industrial park. To focus on the relationship between induced-agglomeration policy and firm survival in industrial parks, we exclude such observations from our analysis.

Using the aforementioned procedures, we obtain a sample of 276,928 observations from 79,667 unique firms.

TABLE 2 Survival age of 79,677 firms in industrial parks

Age (Years)	No. of firms who			Proportion of	
	Were surviving at the beginning of the year	Died during the year	Were censored at the end of the year	All firms still surviving at the end of the year	Firms at the beginning of the year who died by the end of the year
2	79,677	24,923	7,314	0.687	0.313
3	47,440	13,413	4,972	0.493	0.283
4	29,055	2,943	9,748	0.443	0.101
5	16,364	4,630	267	0.318	0.283
6	11,467	1,548	5,053	0.275	0.135
7	4,866	656	1,074	0.238	0.135
8	3,136	360	580	0.210	0.115
9	2,196	355	325	0.176	0.162
10	1,516	160	585	0.158	0.106
11	771	80	242	0.141	0.104
12	449	67	156	0.120	0.149
13	226	13	153	0.113	0.058
14	60	4	35	0.106	0.067
15	21	1	13	0.101	0.048
16	7	0	7	0.101	0.000

Table 2 shows the survival time data of 79,677 firms located in industrial parks during the period from 1998 to 2014. The first column lists the age of firms in years. The second, third, and fourth columns present the number of firms that survived at the beginning of each age period, the number of firms that failed during each age period, and the number of firms that were censored at the end of each age period. The final two columns display the proportion of firms that survived at the end of the age period and the proportion of firms that failed. During the observation period, 49,153 firms ceased operations, while 30,524 firms remained in operation.

3.2 Main variables

3.2.1 TFP

TFP (total factor productivity) is a popular measurement regarding firm productivity (Solow, 1957; Maksimovich, Phillips and Prabhala, 2011; Krishnan, Nandy and Puri, 2014). Scholars often use algorithms, including parametric estimators (Aigner, Lovell and Schmidt, 1977), non-parametric estimators (Kumar, 2006; Charnes, Cooper and Rhodes, 1978; Caves, Christensen and Diewert, 1982), and semi-parametric estimators (Olley and Pakes, 1996; Levinsohn and Petrin, 2003), to estimate TFP. Among these methods, the semi-parametric OP and LP estimators are capable of avoiding simultaneity and selection biasthat may exist in other algorithms (Van, 2012). Among them, the OP method employs firm investment as a proxy variable for unobservable productivity shocks and assumes a monotonic relationship between investment and a firm's output, while also requiring that the investment be greater than zero. However, in practice, many firms have zero investment in the current period due to adjustment costs (Levinsohn and Petrin, 2003), resulting in the loss of a substantial number of samples during the estimation process. The LP method proposed by Levinsohn and Petrin (2003) uses intermediate input as a proxy variable for unobservable productivity shocks to achieve a consistent and valid estimation of input factors while overcoming endogeneity and minimizing sample loss compared to the OP method (Levinsohn and Petrin, 2003; Van, 2012). Consequently, we utilize the LP method in this paper to estimate TFP.

To estimate TFP, we use 1998 as the base year. The income approach is employed to calculate the output of the firm (industrial value added) as suggested by Li and Zhang (2016) and Ren and Sun (2014) (Li and Zhang,2016; Ren and Sun, 2014). We then deflate it with the provincial ex-factory price indices of industrial producers. We define labor input as the number of employees in the firm, as per Jin et al. (2018) (Jin et al., 2018). We measure capital stock by the balance of net fixed assets, which is then deflated using provincial price indices of investment in fixed assets as outlined by Chen et al. (2019). We deflate industrial intermediate input using provincial purchasing price indices for industrial producers, following Ren and Sun's (2014) methodology.

3.2.2 The intensity of induced-agglomeration policy

Financial subsidies and tax incentives are commonly used government support methods worldwide (Ehrlich and Seidel, 2018). In order to attract enterprises to cluster in industrial parks, the Chinese government usually provides tax incentives, financial subsidies and other policy resources to support enterprises (Lu, Wang, and Zhu, 2019). To measure the intensity of induced-agglomeration policy in terms of tax breaks and government subsidies, we rely on Beason and Weinstein's (1993) arguments (Beason and Weinstein, 1993):

(1) Tax breaks. Tax breaks include two parts: value-added tax and income tax

breaks. According to Zhang (2019) (Zhang, 2019), we perform the following calculation: tax break = (applicable rate of firm legal value-added tax) × (value-added of the industry) – (value-added tax payable) + (applicable rate of firm legal income tax) × (total profit) – (firm income tax). Throughout the observed period of our sample, the standard value-added tax rate for general taxpayers in China stood at 17%. The basic corporate income tax rate was 33% before 2008, and 25% from 2008 onwards. We then proceed to calculate the tax incentives for individual firms.

(2) Government subsidies. Government subsidies are measured by the ratio of subsidy income to the total assets of firms (Yu, Han and Li, 2022).

The combined intensity of induced-agglomeration policy is determined through the application of principal component analysis method.

3.2.3 Other covariates

We have taken into account the strategic factors that are relevant for TFP and survival in line with existing literature: (1) *capital intensity* (Takahashi, Mashiyama and Sakagami, 2012; Rath,2018), which is measured by the ratio of net fixed assets to the number of employees; (2) *leverage ratio* (Cochran, Darrat and Elkhal, 2006; Pantzalis,2001), which is measured by the ratio of total liabilities to total assets; (3) *financial constraints* (Petersen and Rajan, 1994; Lin, Sun and Jiang, 2019; Sun and Li, 2012), which is measured by the ratio of interest expense to total fixed assets; (4) *human capital* (Montgomery, 1991; Wagner, 2012), which is measured by the ratio of total wages payable in the year to the number of laborers; (5) *firm size* (Ijiri and Simon, 1964), which is defined as the logarithm of a firm's total assets; and (6) *firm age* (Jovanovic, 1982; Carroll,1983; Fort et al., 2013).There are two ways to express the age of a firm (Wang and Zhao, 2020). The first is the natural age calculated from the year of establishment (Yang and Zhang, 2016), and the second is the business's age indicated by the business's situation and development trend (Gu, Han and Xu, 2000). We use the former to represent the age of a firm and compute it by taking the logarithm of the natural age. The descriptive statistical analysis of the variables is shown in Table 3.

TABLE 3 Descriptive statistics

Variables	Panel A: All sample in industrial parks (N = 667,169)				Panel B: Survival analysis sample (N = 276,928)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
TFP	6.188	1.130	-5.252	12.916	6.199	1.115	-5.252	12.916
Induced_agglomeration_policy	4.891	1.028	0.380	12.156	0.633	3.343	0.000	34.812
Capital intensity	13.560	30.309	0.055	287.618	15.061	34.067	0.055	287.618
Leverage ratio	0.544	0.266	0.006	1.344	0.545	0.270	0.006	1.344
Financial constraints	0.065	0.172	-0.052	1.602	0.068	0.186	-0.052	1.602
Human capital	29.250	45.341	0.644	434.165	32.783	51.020	0.644	434.165
Lnsize	10.500	1.478	2.303	19.427	10.517	1.444	3.871	18.491
Lnage	2.019	0.660	0.000	4.691	1.763	0.577	0.000	2.833

Notes: The maximum Pearson correlation coefficient of all variables is 0.59, the mean variance inflation factor is 1.21, and the maximum value is 1.49, indicating that there is no multicollinearity problem in the model.

4 Empirical results

4.1 TFP distribution of firms located inside and outside industrial parks

Melitz (2003) argued that larger markets tend to attract more firms, resulting in tougher competition, which in turn leads to the exit of low-productive firms due to the "firm selection" effect. This selection effect should lead to a greater left truncation of the distribution of firm productivity in larger areas as the least productive firms exit. Forslid and Okubo (2014) noted that in addition to selection effects (Forslid and Okubo, 2014), both one-sided and two-sided sorting lead the lowest and highest productivity firms to migrate to core areas. However, when examining the TFP distribution of firms in the Chinese Industrial Enterprises Database (CIED), as shown in Figure 1, we can see that the TFP distribution of firms in industrial parks is not left-truncated and does not show characteristics of either one-sided or two-sided sorting. This suggests that the "Darwinian selection" and "sorting effects" cannot explain the productivity differences between firms inside and outside industrial parks.

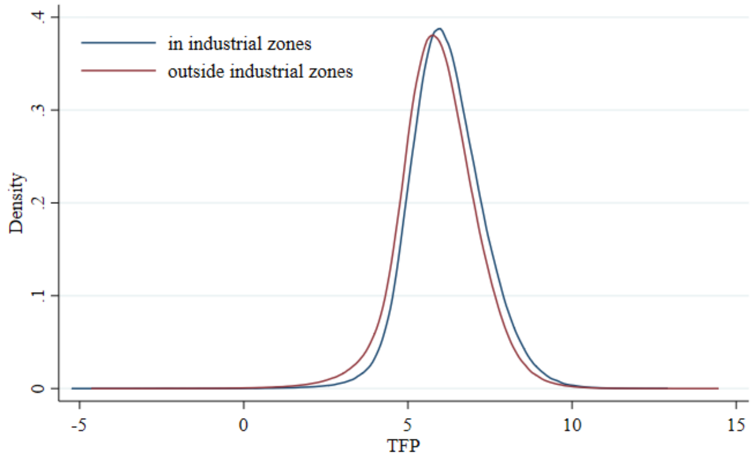

Fig.1 Kernel density plots for all firms

For a detailed analysis, we categorize provinces as “large areas” if their population density is above the median, and as “small areas” if it is below. Figure 2 clearly presents the distribution of TFP among firms located in industrial parks and those outside these parks across both types of regions. According to China’s “National Economic Industry Classification” (GB/T 4754—2017), we divide industrial firms into three main categories: mining, manufacturing, and the production and supply of electricity, heat, gas, and water. Figure 3 illustrates the TFP distribution of firms both inside and outside industrial parks across these three industries. Figures 2 and 3 show results consistent with those presented in Figure 1.

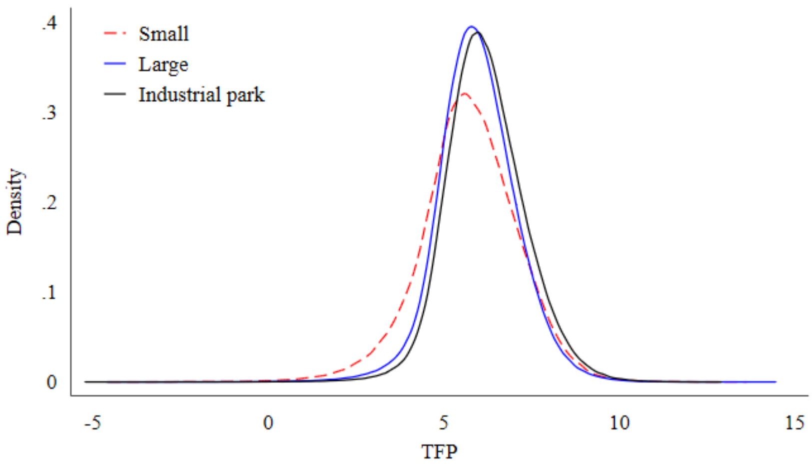

Fig.2 Kernel density plots for the three regions

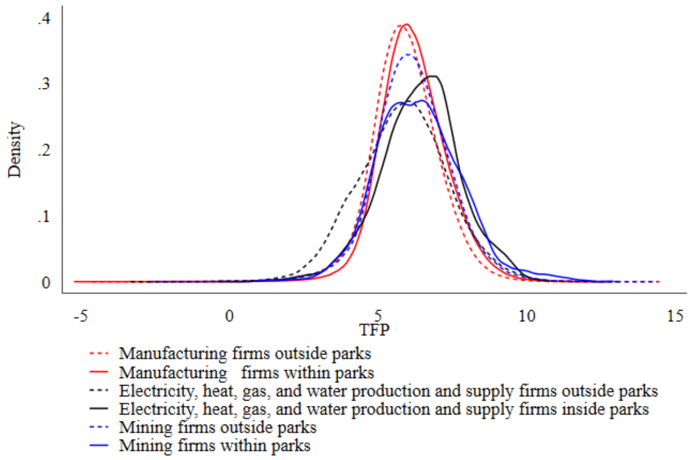

Fig.3 Kernel density plots for the three industries

Figures 1,2 and 3 clearly demonstrate that the TFP curve for firms within industrial parks is significantly shifted to the right compared to those outside, indicating higher productivity levels. Figure 4 further illustrates that the average TFP of firms within these parks consistently exceeds that of their external counterparts each year. However, the TFP gap between firms inside and outside industrial parks generally shows a narrowing trend. Agglomeration effects could account for the higher TFP observed in firms within industrial parks compared to those outside. The sorting effects, as described by Baldwin and Okubo (2006) (Baldwin and Okubo, 2006), suggest that a regional policy can lead to the relocation of the highest productivity firms to the core, while simultaneously causing the lowest productivity firms to move to the periphery. This phenomenon may also help explain the reasons why firms within industrial parks exhibit higher productivity compared to those outside the industrial parks. However, these cannot explain the gradual narrowing of the TFP gap between firms inside and outside the industrial park over time. Apart from factors that positively affect TFP, there must also be other negative factors constraining TFP growth of firms within industrial parks. Investigating the effects of induced-agglomeration policy is the main basis for explaining this phenomenon.

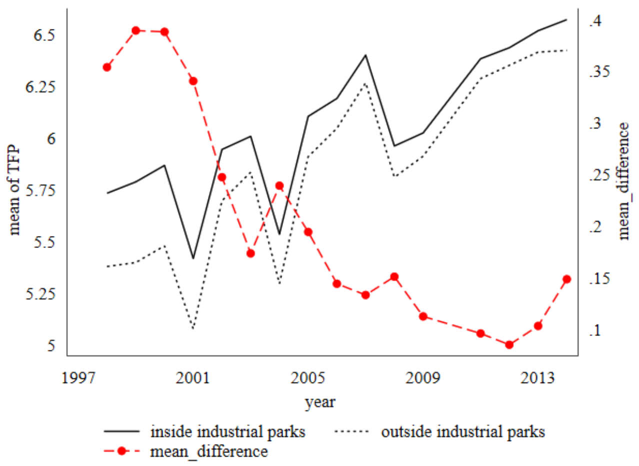

Fig.4 Mean of TFP distributions for all firms

4.2 The effects of induced-agglomeration policy on firm productivity

We use a two-way fixed effects model as our baseline model to examine the effects of induced-agglomeration policy on firm productivity. Since the response to TFP can be dynamic, we also consider the possibility of using event studies (15) and autoregressive distributed lag models (20).

4.2.1 Benchmark estimation

(1) Measures

The construction of the two-way fixed effects model is as follows:

$$\begin{aligned} TFP_{it} = \alpha_0 + \beta_1 induced\_agglomeration\_policy_{i,t} \\ + \beta_2 induced\_agglomeration\_policy_{i,t-1} \\ + \sigma Control_{i,t} + \alpha_i + \delta_t + \gamma_{pro} + \theta_{ind} + \varepsilon_{i,t} \end{aligned} \tag{13}$$

where TFP_{it} is the dependent variable that measures the productivity of firm *i* in year *t*; *induced_agglomeration_policy* indicates the level of intensity of induced-agglomeration policy. *Control* is a set of controls including *capital intensity*, *leverage ratio*, *financial constraints*, *human capital*, *firm size,* and *firm age*. Considering the possible time lag of the effect of *induced_agglomeration_policy* on *TFP*, the first-order lag term of *induced_agglomeration_policy* is added to the model in this paper. The model also includes firm, time, province, and industry fixed effects represented by α, δ, γ, and θ, respectively. ε is the error term. We then use a quantile approach to trace the productivity differences given *TFP* for the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles.

We also allow for a more flexible specification, with firm-fixed effects capable of adjusting over time to absorb more of other variations. Contemporaneous economic phenomena may be loaded on the coefficient of induced-agglomeration policy. Initiatives aimed at encouraging industrial agglomeration could coincide with other innovation-fostering reforms. These factors may potentially lead to a biased estimation of the coefficient of the intensity of induced-agglomeration policy. To address this issue, we estimate our core specification from equation (2) in long differences of 2, 6, or 10 years, that is, for k∈{2,6,10}.

$$TFP_{it} - TFP_{it-k} = \beta(induced\_agglomerati\_policy_{i,t} - induced\_agglomerati\_policy_{i,t-k}) + \sigma\big(Control_{i,t} - Control_{i,t-k}\big) + \widetilde{\delta_t} + \widetilde{\gamma_{pro}} + \widetilde{\theta_{ind}} + \widetilde{\varepsilon_{i,t}} \quad (14)$$

(2) Main results

Table 4 presents the baseline findings, including the results of OLS and quantile regressions. Column (1) shows the raw result obtained from an ordinary least squares regression with the main independent variable. The estimated coefficient of *induced_agglomeration_policy* is -0.159 ($p < 0.01$), suggesting a statistically significant negative association between induced-agglomeration policy and TFP. In column (2), we introduce control variables to the regression model, and the estimated coefficient of *induced_agglomeration_policy* is -0.137 ($p < 0.01$). This indicates that induced-agglomeration policy remains negatively associated with TFP.

As OLS analysis focuses on "the average effect for the average firm", we employ a quantile approach to trace TFP differences and report the results for TFP at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles. In columns (3)-(7), the coefficients of *induced_agglomeration_policy* are all negative and significant, with the coefficients at higher quantiles yielding lower absolute values. This suggests that the negative effect of *induced_agglomeration_policy* on TFP decreases as firm productivity increases. In other words, more productive firms experience less TFP loss from induced-agglomeration policy. Hypothesis 1 is supported.

TABLE 4 Effects of induced-agglomeration policy on TFP (OLS and Quantile regression)

	OLS	Quantile regression

Variables	(1)	(2)	(3) q10	(4) q25	(5) q50	(6) q75	(7) q90
Induced_agglomeration_policy	-0.159***	-0.137***	-0.170***	-0.159***	-0.136***	-0.116**	-0.106*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.093)
L.Induced_agglomeration_policy	-0.027***	-0.012***	-0.011	-0.011	-0.012	-0.012	-0.013
	(0.000)	(0.000)	(0.748)	(0.670)	(0.695)	(0.798)	(0.831)
Capital intensity		-0.004***	-0.004**	-0.004***	-0.003**	-0.003	-0.003
		(0.000)	(0.034)	(0.009)	(0.042)	(0.252)	(0.378)
Leverage ratio		-0.304***	-0.358**	-0.340**	-0.302**	-0.270	-0.253
		(0.000)	(0.036)	(0.010)	(0.047)	(0.271)	(0.401)
Financial constraints		0.229***	0.168	0.189	0.231	0.268	0.287
		(0.000)	(0.451)	(0.274)	(0.245)	(0.401)	(0.464)
Human capital		0.004***	0.004***	0.004***	0.004***	0.004***	0.004**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.011)
Lnsize		0.326***	0.362***	0.349***	0.325***	0.303***	0.292**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.010)
Lnage		-0.031***	0.143	0.083	-0.038	-0.143	-0.197
		(0.009)	(0.428)	(0.553)	(0.814)	(0.581)	(0.535)
Constant	6.733***	3.780***					
	(0.000)	(0.000)					
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	415726	415726	415726	415726	415726	415726	415726
adj. R^2	0.152	0.235					

Notes: p-values in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 5 reports the estimated results from the long-difference specification in equation (14). These estimates are also significantly negative, as indicated by the coefficients of *induced_agglomeration_policy*, which are -0.150 for the two-year difference, -0.175 for the six-year difference, and -0.172 for the ten-year difference.

TABLE 5 Long-difference specifications

Variables	(1) Panel A:2-year long difference	(2) Panel B:6-year long difference	(3) Panel C:10-year long difference
ΔInduced_agglomeration_policy	-0.150***	-0.175***	-0.172***
	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes
Constant	6.065***	13.024*	896.075
	(0.000)	(0.051)	(0.673)
Year fixed effects	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes
Observations	217,014	18,740	2432
adj. R^2	0.201	0.228	0.227

Notes: p-values in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

In order to visualize these results, we also plot binned scatter plots of policy-induced agglomeration against TFP. Both firm productivity and induced-agglomeration policy variables are residualized against firm and year fixed effects as well as lagged *capital intensity*, *leverage ratio*, *financial constraints*, *human capital*, *lnsize*, and *lnage*. Figure 5 shows a consistent negative long-liner relationship between induced-agglomeration policy and TFP, further confirming Hypothesis 1.

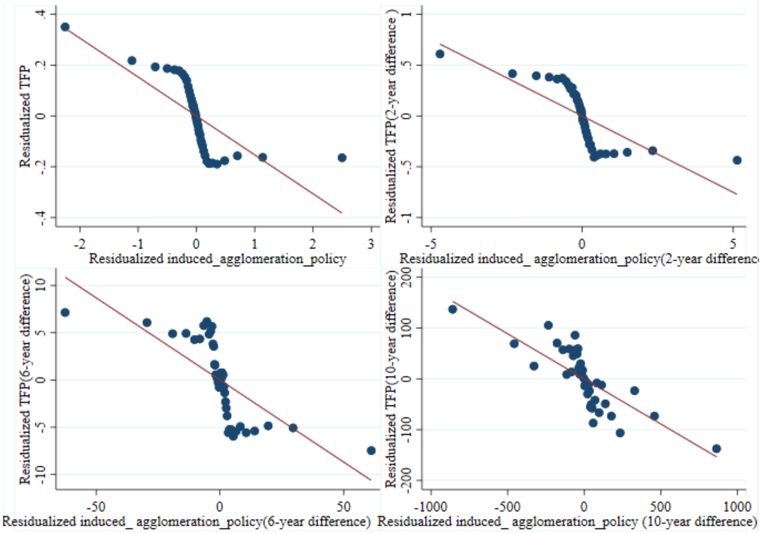

Fig.5 Binned Scatters

Note: This figure displays scatter plots illustrating the effect of induced-agglomeration policy at the firm level. Both the horizontal and vertical axes are residualized against firm and year fixed effects, as well as lagged *capital_intensity*, *leverage_ratio*, *financial_constraints*, *human_capital*, *lnsize*, and *lnage*.

(3) Robustness tests

For robustness testing, this section divides the total sample into two sub-samples: developed regions and underdeveloped regions, based on whether the actual regional GDP is above the average, and performs regression estimates separately. The estimation results are shown in columns (1) and (2) of Table 6. The results show that in developed regions, the marginal impact of induced-agglomeration policy on firm TFP is -0.118 ($p<0.01$), with a 95% confidence interval of [-0.121, -0.115]. In underdeveloped regions, the marginal impact of induced-agglomeration policy on firms TFP is -0.170 ($p<0.01$), with a 95% confidence interval of [-0.173, -0.167]. There is no overlap in the confidence intervals of the two sub-samples, indicating a significant difference in the estimated values of the core explanatory variable between the sub-samples. We further examine the heterogeneity between the estimated coefficients using Fisher's permutation test, which shows an empirical p-value of 0.000. This confirms that there is a significant difference in the impact of the induced-agglomeration policy on firm

TFP across regions with different levels of economic development. Additionally, the negative impact is more pronounced in less developed regions. In other words, compared to developed regions, the impact of the induced-agglomeration policy on firm TFP is more significant in underdeveloped regions. Thus, Hypothesis 2 is confirmed.

Reverse causality and omitted variables are the main reasons that might cause endogeneity issues in this paper. This paper employs instrumental variables to address potential reverse causality. We select the third and fourth lags of *induced_agglomeration_policy* as joint instrumental variables and use 2SLS for estimation. The estimation results are shown in columns (3) and (4) of Table 6. In the first-stage regression, the coefficients of the instrumental variables are both significant, indicating that the instrumental variables meet the relevance condition. Additionally, we conduct the weak instrumental variable test and find that the Wald statistic value of 2873.191 is greater than 19.93 (10% significance level). The results indicate that our instrumental variables do not have the problem of weak instrumentals. In the second-stage regression, the coefficient of *induced_agglomeration_policy* is -0.178 (p=0.000), which is significantly negative, suggesting that the instrumental variable regression results still support the baseline regression results.

TABLE 6 Effects of induced-agglomeration policy on firm productivity

Variables	(1)	(2)	(3)	(4)
	split sample		IV-2SLS	
	Above-average GDP	Below-average GDP	First Stage *Induced_agglomeration_policy*	Second Stage *TFP*
Induced_agglomeration_policy	-0.118***	-0.170***		-0.178***
	(0.000)	(0.000)		(0.000)
L3.Induced_agglomeration_policy			0.313***	
			(0.000)	
L4.Induced_agglomeration_policy			0.187***	
			(0.000)	
Controls	Yes	Yes	Yes	Yes
Constant	3.765***	3.102***	3.978***	3.097***
	(0.000)	(0.024)	(0.000)	(0.000)
Firm fixed effect	Yes	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
N	265,907	401,262	116,304	116,304
adj. R^2	0.183	0.264		
Empirical p-value	0.000			
Kleibergen-Paap rk LM statistic			3606.986	

	(0.000)
Kleibergen-Paap Wald rk F statistic	2873.191
	[19.93]
Hansen J statistic	0.804
	(0.370)

Notes: p-values in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01; Empirical p-value aims to test whether there is a significant difference in the regression coefficients of the *induced_agglomeration_policy* in the grouped regression results. This is obtained by repeatedly sampling 100 times using the bootstrap-based Fisher's permutation test; [ ] indicates the 10% critical value for the Stock-Yogo weak instrument test.

We also perform a sensitivity analysis using an omitted variable bias framework to address the potential omitted variable problems. While we include variables that may affect firm TFP based on previous studies, it is still challenging to claim that there are no unobserved confounding variables. To ensure the validity of the regression results, we use the sensitivity analysis tool proposed by Cinelli et al. (2020) to determine how strong the unobservable confounders would be required to overturn the findings of this study (Cinelli, Ferwerda and Hazlett, 2020). Since *human capital* is the main variable affecting TFP and is significantly positively related to TFP (P<0.01) in all the above models, we select it as the comparison variable to test the validity of our previous results when the intensity of the omitted variable is *n* times as strong as the particular variable. We draw the coefficient β and the *t*-statistic contour map (Figure 6) to explore the possible changes in the estimated results caused by missing variables with different intensities. The results show that the original estimation effects remain negative even if the unobserved confounders are three times as strong as the observed covariate *human capital*. In addition, the null hypothesis of zero effect would not be rejected at the 5% significance level even if confounders are three times as strong as *human capital*. Therefore, we conclude that our results are robust.

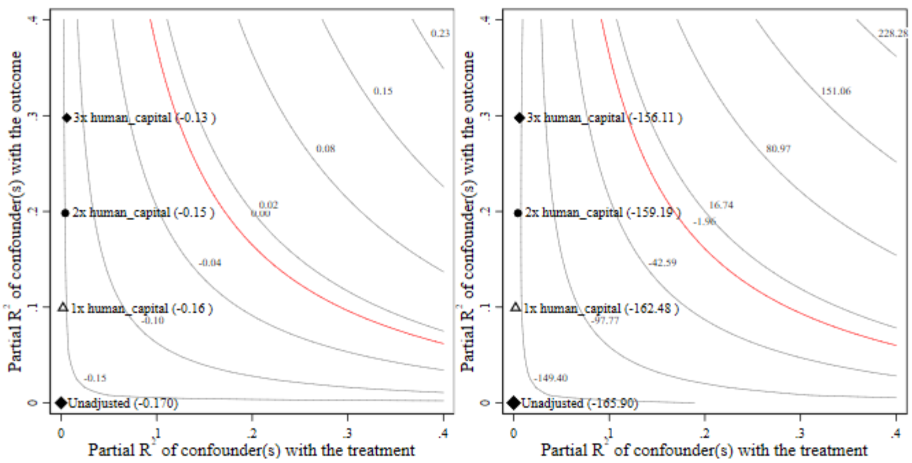

Fig.6 Sensitivity contour plots of point estimates (left) and t-values (right)

4.2.2 Event studies

To provide visual evidence of the dynamic negative total effects on firm TFP, this study employs event study methodology to estimate the impact of the event—firms entering industrial parks and benefiting from preferential policies—on their TFP. The event study specification can be expressed as follows[71]:

$$TFP_{it} = \alpha_0 + \sum_{j=2}^{J} \beta_j (\text{Lead } j)_{it} + \sum_{k=1}^{K} \gamma_k (\text{Lag } k)_{it} + X_{it}'\Gamma + \alpha_i + \delta_t + \gamma_{pro} + \theta_{ind} + e_{it} \tag{15}$$

Where *i* and *t* index the firm and year, respectively; X_{it} is a set of time-varying controls including *capital intensity*, *leverage ratio*, *financial constraints*, *human capital*, *firm size,* and *firm age*; α_i, δ_t, γ_{pro} and θ_{ind} are firm, year, province, and industry fixed effects, respectively; and e_{it} represents idiosyncratic shocks. The coefficients of the lags and leads correspond to the trend of the event's effect over different time periods.

In equation (15), leads and lags to the event of interest are defined as follows:

$$(\text{Lead } J)_{it} = \mathbb{1}[t \leq Event_i - J] \tag{16}$$

$$(\text{Lead } j)_{it} = \mathbb{1}[t = Event_i - j] \; for \; j \in \{1, \cdots, J-1\} \tag{17}$$

$$(\text{Lag } k)_{it} = \mathbb{1}[t = Event_i + k] \; for \; k \in \{1, \cdots, K-1\} \tag{18}$$

$$(\text{Lag } K)_{it} = \mathbb{1}[t \geq Event_i + K] \tag{19}$$

$Event_i$ is a variable that records the entry of firm *i* into an industrial park during time period *t*, with this event occurring at different times across different firms. Leads and lags are binary variables indicating the number of periods that a given firm is away from entering the industrial park in respective time periods. *J* and *K* leads and lags are included respectively, and, as indicated in equations (16) and (19), final leads and lags "accumulate" leads or lags beyond *J* and *K* periods. A single lead or lag variable is omitted to capture the baseline difference between firms where the event does and does not occur. In specification (15), as standard, this baseline omitted case is the first lead (one period prior to the firm entering the industrial park), where $j = 1$. Here, we include 3 leads and 10 lags, denoted as $J = 3$ and $K = 10$, respectively. Lead and lag variables (exclusively) are switched on for periods in which the "Time to Event" exceeds 3 leads or 10 lags.

Figure 7 shows the estimated coefficients of the dummies, with 95% confidence intervals indicated by the vertical lines. To capture the baseline difference between firms where the event does and does not occur, we omit the first lead. We note before the firm entered the industrial park, the estimates are mostly insignificantly different from zero. However, after the firm entered the industrial park, the coefficients turn negative and statistically significant. This suggests a negative effect of induced-agglomeration policy as early as the first calendar year. Consistent with the results obtained from the long-difference specification in equation (14), we observe a lag in the effect of induced-agglomeration policy on TFP, with the strongest effects appearing six or seven years later. This aligns with the conclusions presented in Figure 7, after the sixth year in the industrial park, the TFP gap between firms inside and outside the park increases dramatically.

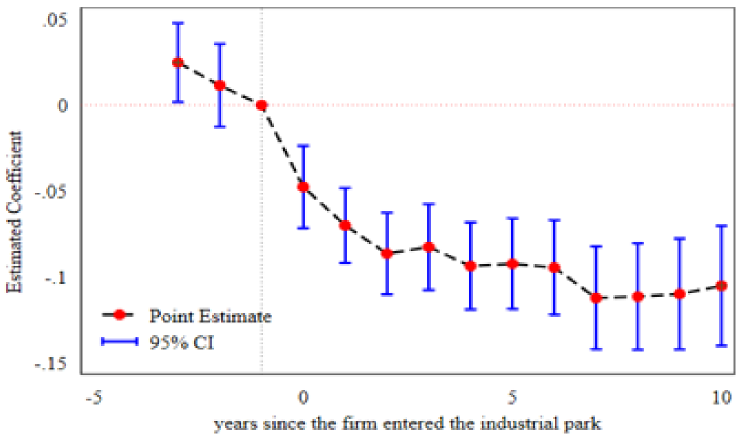

Fig.7 Dynamic effects of induced-agglomeration policy on TFP

4.2.3 Longer-run effects of induced-agglomeration policy

To investigate the longer-term dynamic impacts of induced-agglomeration policy on TFP, we utilize an ARDL (1,8) model, which is capable of distinguishing the effects of different leads and lags of induced-agglomeration policy. Our analysis involves estimating the subsequent regression equations:

$$TFP_{it} = \lambda TFP_{i,t-1} + \sum_{l=-3}^{8} \beta_l \, induced\_agglomeration\_policy_{i,t-l} + \sigma \Delta Control_{i,t-1} + \delta_t + \varepsilon_{it} \tag{20}$$

where δ_t is the year fixed effect, and *Control* is a set of controls including *capital intensity*, *leverage ratio*, *financial constraints*, *human capital*, *lnsize*, and *lnage*. Over the longer range, serial correlation in the error terms ε_{it} might be more significant. To address this, we cluster at the province level.

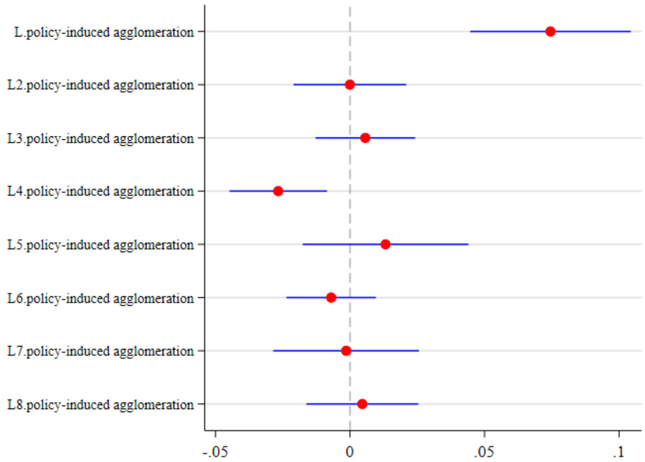

Fig.8 Short-run effects of induced-agglomeration policy

As depicted in Figure 8, the short-term impacts may not all be statistically significant. Nevertheless, our focus lies on the long-term cumulative effect. Specifically, we examine the cumulative effects B_l of an *induced_agglomeration_policy* shift in year *t* on TFP by year $t + l$,where $l \in \{-3,..., 8\}$. We illustrate this in the plot below:

$$\mathcal{B}_l = \underbrace{\left[\sum_{\tau=-3}^{l} \beta_l\right]}_{\substack{Effect\, from \\ t-3 \\ though\, t+l}} - \underbrace{\left[\sum_{\tau=-3}^{-1} \beta_l\right]}_{\substack{Renormalizing \\ to\, be\, relative \\ to\, year\, t-l}} \tag{21}$$

Figure 9 displays estimates obtained from the distributed lag model outlined in Equation (21). We plot $\mathcal{B}_l$, representing the cumulative effect of a one-unit change in *induced_agglomeration_policy* in year *t* through year $t + l$. Notably, we normalize the value of the zero-lag shift to zero. The dashed lines represent 95% confidence intervals calculated using standard errors clustered at the province level. Figure 9 suggests no detectable pretrends in TFP around *induced_agglomeration_policy* changes. Nonetheless, our analysis indicates that, over the longer run, *induced_agglomeration_policy* changes have a negative effect on firm productivity.

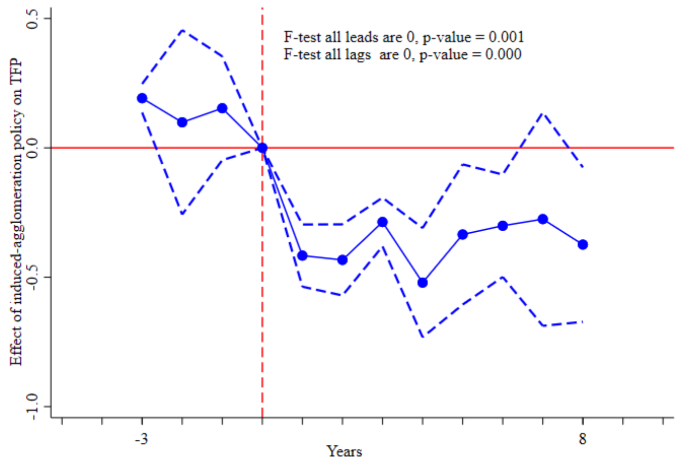

Fig.9 Distributed lag regressions

4.3 The effects of induced-agglomeration policy on firm survival

To investigate the effects of induced-agglomeration policy on firm duration, we develop a survival analysis model. Survival analysis models often used by scholars include the continuous-time Cox proportional hazards model and the discrete-time survival analysis model (Clarke and Tapia-Schythe, 2021; Cox, 1972). We opt to use a discrete-time complementary log-log (Cloglog) survival model for econometric analysis, similar to studies conducted by Hess and Persson (2012) and Esteve-Pérez et al. (2012). This approach effectively overcomes issues such as the ties problem, unobserved heterogeneity, and the proportional hazards assumption in a continuous-time Cox model.

The core of survival analysis is to estimate the probability of a firm's "death" in a given time interval $[t_k, t_{k+1}]$ (k = 1, 2, . . ., 15, and t_1 = 1998), which is known as the discrete-time hazard rate (h_{ik}). In this study, a firm is considered to have "failed" if it appears in the CIED during the year t but does not appear in any subsequent year until 2014. The fundamental regression equation is presented below:

$$h_{ik} = P\left(T_i < t_{k+1} \middle| T_i \geqq t_k, x_{i,k}\right) = F\left(x'_{i,k}\beta + \gamma_k\right) \tag{22}$$

where T_i is a continuous, non-negative random variable that represents the survival time of firm i; x_{ik} is a vector of possibly time-varying covariates; γ_k is a function of baseline hazard; and $F(\cdot)$ is the distribution function of h_{ik} ($0 \leq h_{ik} \leq 1$).

To estimate the discrete-time survival model, we use a technique introduced by Jenkins (1995) (Esteve–Pérez, Requena–Silvente and Pallardó–Lopez, 2012), where we introduce a binary outcome variable, y_{ik}, which takes on a value of "1" if firm i is observed in the CIED during the k^{th} time interval, and "0" otherwise. We then construct the following log-likelihood function for the observed data, as outlined by Hess and Persson (2012):

$$lnL = \sum_{i=1}^{n} \sum_{k=1}^{t} \left[y_{i,k} \ln\left(h_{i,k}\right) + \left(1 - y_{i,k}\right) \ln\left(1 - h_{i,k}\right) \right] \tag{23}$$

The equation (23) can be estimated using the binary choice model. The functional form of h_{ik} can generally be set as the normal distribution, logistic distribution, or extreme value distribution, corresponding to the *Probit* model, *Logi*t model, and *Cloglog* model, respectively. In our sample data, the explanatory variable y_{ik} contains a large number of "0" and a relatively small number of "1", which may lead to rare event bias. To address this issue, we chose the *Cloglog* model and set the model as follows:

$$\begin{aligned} Cloglog[1 - h_t(X|v)] &\equiv \log\{-\log[1 - h_t(X|v)]\} \\ &= \beta induced\_agglomeration\_policy + \rho Control + \gamma_t \\ &\quad + u \end{aligned} \tag{24}$$

where X is a set of explanatory variables; γ_t is the interval baseline hazard ratio; u, transformed into $\log(v)$, is the unobserved heterogeneity; and *Control* includes relevant explanations for the duration, such as *TFP*, *capital intensity, leverage ratio*, *financial constraints*, *human capital*, *firm size*, and *firm age*. Additionally, we include fixed effects for firm, year, industry, and province. To confirm the difference in coefficients between groups, we introduce two dummy variables R_{it} and D_{it}. R_{it} equals "1" if firm i is located in the eastern regions, and "0" otherwise. D_{it} equals "1" if firm i is located in the regions with above-average GDP, and "0" otherwise.

The empirical results are presented in Table 7. Column (1) of Table 7 shows that the estimated coefficient of *induced_agglomeration_policy* is -0.063 ($p<0.01$), which is significantly negative, indicating that induced-agglomeration policy reduces firm risk and extends firm longevity. To investigate whether there are regional differences in the impact of induced-agglomeration policy on firm hazard rates, we divide the total sample into two sub-samples based on whether the regional GDP is above the mean. We conduct regression estimates for developed and underdeveloped regions, as shown in columns (2) and (3) of Table 7. The results indicate that the estimated coefficients of *induced_agglomeration_policy* for the developed and underdeveloped regions are -0.046 (p<0.01) and -0.069 (p<0.01), respectively. The Fisher's combination test shows an empirical p-value of 0.000 for the difference in coefficients between the groups, indicating a significant difference in the impact of induced-agglomeration policy on firm hazard rates between economically developed and underdeveloped regions. The effect of induced-agglomeration policy on firm survival is more pronounced in underdeveloped areas of China than in developed areas, confirming Hypothesis 3.

TABLE 7 Discrete-time Cloglog model estimating results

Variables	(1) Full sample	(2) Above- average GDP	(3) Below- average GDP
Induced_agglomeration_policy	-0.063^{***} (0.000)	-0.046^{***} (0.000)	-0.069^{***} (0.000)
Controls	Yes	Yes	Yes
Constant	4.307^{***} (0.000)	2.291^{***} (0.000)	4.254^{***} (0.000)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	246,271	109,764	136,507
Log likelihood	-92,003.491	-41,718.677	-49,384.831
Empirical p-value		0.000	

Notes: p-values in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01; Empirical p-value aims to test whether there is a significant difference in the regression coefficients of *induced_agglomeration_policy* in the grouped regression results. This is obtained by repeatedly sampling 100 times using the bootstrap-based Fisher's permutation test.

5 Discussion and Limitations

Building on the research discussed earlier, we can delve deeper into the analysis of induced-agglomeration policy on firm TFP. The TFP distribution curve for firms within industrial parks shifts rightward compared to those outside, indicating superior TFP performance. These firms also exhibit a mean TFP significantly higher than their counterparts outside the parks. However, over time, the disparity in mean TFP between these two types of firms gradually diminishes. Our observations validate the significant reason explaining this phenomenon, which is that the induced-agglomeration policy has a negative impact on firm TFP, thereby hindering the improvement of firm productivity. This may be due to government efforts exceeding optimal levels, leading to an increase in the number of industrial parks, overcrowding among them, and an oversupply of space within these parks. Our further research found that, supported by favorable policies such as financial subsidies, tax incentives, and preferential land supply, many inefficient firms that should have been eliminated by the market have managed to survive within industrial parks. This also explains why the TFP distribution within industrial parks is not left-truncated. The prolonged presence of inefficient firms not only weakens the competitive elimination mechanism among firms to some extent, leading to a misallocation of market resources, but also impacts the overall production efficiency and developmental quality of industrial parks, thereby impeding the sustainable development of industrial parks. Therefore, the optimal intensity of China's induced-agglomeration policies remains to be further explored in future research. This exploration is crucial as the current analysis highlights a clear gap in understanding how policy intensity can be fine-tuned to avoid oversaturation and promote high-quality, differentiated development in industrial parks across different regions.

Another significant limitation of this study pertains to the availability and scope of data. The industrial enterprise database only contains records dating back to 1998, which significantly constrains our ability to investigate the early development phases relevant to our topic. The period from 1979 to 1999 was marked by robust growth in Chinese industrial parks, and a thorough analysis of this era would more effectively unveil the nonlinear impacts of combined influences within these parks. While the effects of induced-agglomeration policies have been negative, the aggregate impact during the early stages of development in Chinese industrial parks was undoubtedly positive. Despite data limitations that restrict our capacity to fully track the dynamic changes in TFP within these parks during this time, the research presented here remains vitally important. Given the current developmental state of industrial parks in China and the government's strong commitment to resolving the challenges they face, it is evident that the trajectory of industrial park development in China has strayed from its former path of prosperity.

The third limitation of this paper is in the construction of the theoretical model, where it is assumed that there is a positive correlation between the decline in the price of capital inputs and the intensity of induced-agglomeration policy. It is also assumed that the final product prices are determined by market supply and demand, and following the study by Acemoglu (2002), TFPR is defined as the price of final product and TFP. These assumptions are mainly based on observations of the Chinese government frequently using direct policy tools such as fiscal subsidies and tax incentives to promote industrial agglomeration. While these assumptions streamline the model analysis and capture certain aspects of Chinese policy practices, we may not fully account for the potential impacts of policies on other economic variables, such as product prices and wage levels. Future research should delve deeper into the interactions between policies and a broader range of economic factors, thereby offering a more comprehensive and accurate foundation for policy formulation.

We conducted further analysis on the changes in TFP for firms before and after they entered and exited industrial parks. Besides agglomeration effects and policy-induced effects, other factors also influence firm TFP, with the impact of physical relocation being particularly noteworthy. Physical relocation involves a complex process of resource reallocation, production process adjustments, and market relationship restructuring, thus leading to a negative impact on firm TFP. Compared to the impact of other factors on firm TFP, the negative effects of physical relocation are relatively short-lived and can be repaired relatively quickly as firms adjust during the adaptation process. According to Figure 10, firms entering the industrial park initially exhibited an upward TFP trend, indicating that despite various influences, their TFP generally improved. Nevertheless, after the 12th year, TFP declined, suggesting that the adverse effects of policy-induced agglomeration outweighed the positive impacts. Further analysis of firms exiting industrial parks shows, as depicted in Figure 11, a noticeable decline in average TFP levels post-departure, with the negative effects of physical relocation being more pronounced. However, from the second year after exiting, there was a significant improvement in TFP levels. These results suggest that not all firms are suitable for entering industrial parks, and fully considering firm heterogeneity is crucial for further optimizing China's inducement policies for agglomeration. This underscores the importance of our subsequent research efforts.

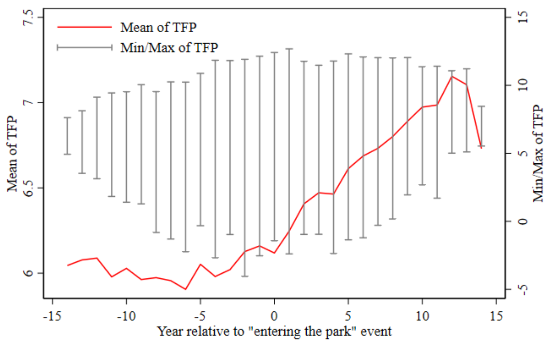

Fig.10 TFP changes for entered firms

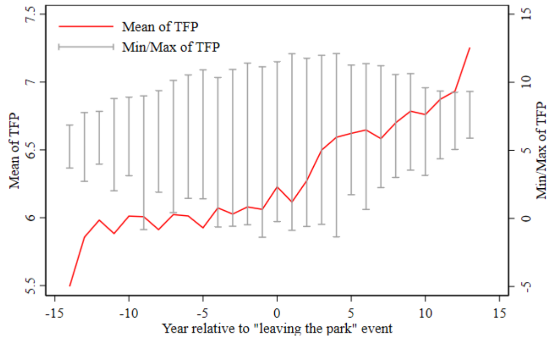

Fig.11 TFP changes for exited firms

6 Conclusions

In this study, we utilized firm-level data from the Chinese Industrial Enterprises Database (CIED) spanning from 1998 to 2014 to investigate the impact of induced-agglomeration policies on the productivity and survival of firms within industrial parks. Contrary to the prevailing consensus in existing literature that agglomeration generally enhances productivity, our research findings suggest that induced-agglomeration policy in China can have negative effects, particularly in less developed regions. This discovery challenges the universality of employing a one-size-fits-all approach in policy design. Moreover, our results underscore the importance of a nuanced understanding of policy impacts across different economic contexts. Future research could further explore the impact of inducement policies on firms by expanding the sample range, incorporating more diverse data sources, employing more complex models, and conducting comparative analyses across countries and periods. This would not only help to verify the validity of the results of this study but also provide richer perspectives for understanding the mechanisms of government agglomeration policies in different economies, offering solutions for policy optimization under various backgrounds.

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Author contributions

Jianxiu Wang comprehensively oversaw the overall direction and approach of the research. Dandan Hou was responsible for the experimental design and data collection sections of the paper. Shunchang Zhong primarily handled the theoretical analysis and model building parts of the paper. Rongwang Guo mainly took on the literature review and auxiliary experimental work in the paper. All authors contributed to the article and approved the submitted version.

Funding

This study was funded by The National Social Science Fund of China [Grant numbers 20BJL116].

Competing interests

All authors declare that no conflict of interest exists.