Firm Entry and the Growth of The Science Parks based on Energy Innovation: Evidence from Beijing Zhongguancun Science Park in China

Jianguo Wang[1], Hongchun Yu[1], Jingjing Wang[1*]

[1]Business School, Beijing Information Science and Technology University, Beijing, China

[*]Corresponding author: Jingjing Wang, Email: jingjing_wang@bistu.edu.cn

Abstract: Understanding the micro-level dynamic mechanism of economic growth of the science park is of great significance to the theory of regional economics and the policies to promote innovation. Based on the novel firm-level data from 2005 to 2015 on Beijing Zhongguancun Science Park (Z Park for short) in China, this paper investigates the dynamic impacts of firm entry on Z Park's growth, measured by productivity and size, respectively, and an extended analysis is conducted from the perspective of energy utilization and innovation. By employing the DOP and EEKT decomposition methods, we first find that new entrants have a lower TFP and output than incumbent firms. However, in the following years, the relative growth rates of them are faster and gradually converge to or even exceed the latter in both the TFP and output level. Second, the new enterprises do not significantly promote the annual TFP growth of Z Park in the year of entry but finally enhance the TFP growth on average during these ten years. Third, different from the impact on the growth of TFP in Z Park, new entrants contribute substantially to the annual output growth of Z Park in the year of entry, and this effect has further increased on average. The analysis combined with energy utilization shows that with the entry and growth of new enterprises, they are gradually showing potential in improving energy efficiency and innovating energy technology. These findings provide valuable insights into the dynamics of economic growth in science parks and suggest potential strategies for promoting innovation for policymakers.

Keywords: Firm entry; Output; TFP (Total Factor Productivity); Zhongguancun science park; Energy innovation

1 **Introduction**

A science park usually refers to a designated area where economic activities between enterprises are highly interconnected, and is a hub for talent migration. It is where cutting-edge knowledge is generated, and key technological innovations are highly intensive. The growth and success of globally renowned science parks—such as Research Triangle Park, Boston's Route 128, and Silicon Valley in the United States—could be attributed to knowledge spillovers, specialized labor markets, the influx of talented individuals, industrial and supply chain integration, global networks, etc. (Hobbs, Albert, and Scott, 2016; Kerr and Robert-Nicoud, 2020). However, China's science parks represent a hybrid model, characterized by both science parks in Western countries and industrial parks in China, which emphasize both innovation-driven development and industry-size growth (Wang and Zhu, 2018). Since the foundation of Z Park, the first science park in 1988, the national science parks have emerged as a vital force driving national and regional economic growth, transforming the mode of economic growth, and serving as key platforms for implementing innovation-driven development strategies in China. By 2022, there were 177 national science parks across the country, with a total number of 205,848 enterprises, which have been created business revenue of 53.4 trillion yuan and added value of 17.3 trillion yuan, accounting for 14.3% of the national GDP. The R&D expenditure of these enterprises was 1.1 trillion yuan, which accounts for 36.4% of the R&D expenditure of all the enterprises in China. Therefore, an in-depth exploration of the dynamic mechanism of Z Park is crucial for understanding the Chinese characteristics science parks and further their role in leading and driving regional development.

Current studies on the growth mechanisms of China's science parks are mainly based on aggregate data and explored from the perspective of factor inputs in the production function of a representative firm. However, this approach fails to illuminate the micro-foundations of growth dynamics and overlooks the role of innovation and entrepreneurship. Notably, China's science parks have progressed three distinct stages of development (Wang and Zhu, 2018), each with unique pattern of TFP and output growth. The first venture stage (1991 to 2000) saw rapid output expansion, driven mainly by factor inputs instead of technological progress, only accounting for 4% of the output growth (Luo, 2006). In the second venture stage (2001 to 2010), the contribution of TFP or technological progress to the growth of science parks increased significantly, while the growth rate of science parks measured by output has slowed. In contrast, during the third venture stage (since 2011 and after), despite more policies to support indigenous innovation-driven development, TFP growth showed a sustained decline from 2011 to 2018 (Sun and Wang, 2020). Our research investigates the driving forces of the growth of the science parks by using the firm-level micro data on enterprises of Z park from 2005 to 2015, which is across the second and third stages, aim to provide a comprehensive analysis of the growth dynamics of science parks.

Other studies explain the growth of science parks in China through capital accumulation, R&D investment, human capital, financial capital, market demand, government policies, and so on (Zhu and Tann, 2005; Zhang and Wu, 2012; Sun and Wang, 2020). This paper, however, focuses on the perspective of firm entry since firm entry or exit is considered as a critical micro-level driver of economic growth at regional, industrial, and national levels. Endogenous growth theories typically use the production function that analyzes the aggregate relationship between factor inputs and the output of a representative firm. Given that this approach overlooks the dynamic effects arising from firm heterogeneity, Neo-Schumpeterian growth theory underscores the creative destruction process driven by heterogeneous firms, highlighting the role of firm entry and exit in economic growth (Klette, Samuel, 2004; Acemoglu et al., 2018). The continuous entry of firms enhances overall market productivity by attracting highly productive firms and eliminating firms with low productivity through market competition. This market selection process, driven by competition, indicates that new firms are more efficient than incumbents. However, in practice, start-up costs and learning curves often prevent new firms from immediately reaching the productivity frontier (Foster, Haltiwanger, and Syverson, 2016). Therefore, whether new entrants have higher efficiency than incumbents deserves further empirical studies.

Many empirical studies have been conducted to explore the impact of firm entry and exit on aggregate productivity growth at the industry or national levels, but they have not achieved consensus yet. Some studies contend that, while the net effect of firm entry and exit is generally positive, new firms show no significant short-term productivity advantage over the incumbents. The productivity of new entrants is often lower than that of the incumbent firms, resulting in a minimal or even negative contribution of firm entry to aggregate productivity in the short run (Baily, Hulten, Campbell, 1992; Foster, Haltiwanger, Krizan, 2001; Brandt, Biesebroeck, Zhang, 2012; Mason, Robinson, Rosazza Bondibene, 2016). In contrast, other studies suggest that firm entry is a significant driver of productivity growth at both national and industry levels in the long run due to the selection and post-entry learning effect (Foster, Haltiwanger, Syverson, 2008). These long-term studies are crucial in understanding the dynamic impact of firm entry and exit. The creative destruction process driven by new firms not only boosts overall productivity but also leads to creating and shutting production units. Firm entry plays a crucial role in the GDP expansion of a country or output expansion of a specific industry through mechanisms distinct from those driving productivity growth. Studies on the manufacturing sectors in the United States and Canada reveal that while new firms are initially small, they progressively account for a large share of the market in terms of total firm numbers and sales within just a few years (Dunne, Roberts and Samuelson, 1988; Baldwin and Gorecki,1991). Similarly, research on China's manufacturing sector indicates that although new firms only contribute to an average of 7.5 percent of the sector's value-added, firm entry is a key driver of the annual growth of value-added, accounting for an average of 46.3 percent (Li and Jiang, 2015). Studies on the effect of firm entry on the growth at the science park level are pretty limited, and our research considers both the productivity and output in measuring the growth of the science park due to the mixed findings above.

Based on the unique firm-level panel data of Z Park from 2005 to 2015, this paper empirically investigates the dynamic impact of firm entry on the TFP and output growth of national science parks in China by employing decomposition methods. The main conclusions are as follows: First, new entrants' TFP and output levels are initially lower than those of incumbent firms, but the relative growth rate of both TFP and output thereafter is higher. As a result, in terms of TFP and output level, the gap between new firms and incumbents gradually narrows, or even the former exceeds the latter. Second, as new firms' TFP level is lower than that of incumbent firms in the science park for the first year, they drag down the TFP growth. Its contribution rate is -27.9%. Due to the learning effect and market competition, their contribution to productivity growth gradually turns positive, with a cumulative contribution rate of 5.4%. So, incumbent firms mainly contribute to TFP growth instead of new entrants. Third, different from their impact on TFP growth, new firms significantly contribute to the annual output growth of the science park in the year of entry, and its contribution rate is 56.3%. Although their impacts decline annually later, the ten-year cumulative contribution is summed at 83.1%, which indicates that new entrants mainly contribute to output growth. Further analysis across various industries validates the role of firm entry in the TFP and output growth of science parks. These conclusions are robust across different TFP decomposition methods and various size and productivity indicators.

The paper contributes to the theoretical and empirical literature in three ways. First, from the perspective of firm entry, we empirically investigate the driving force of science parks in China by using unique firm-level micro data. Unlike current studies that mainly use aggregate data, this approach allows us to explore the micro-level heterogeneity between new entrants and incumbent enterprises. Second, the paper highlights the distinction between the role of firm entry in affecting the productivity and size growth of Z Park. This distinction is so important that it enables us to capture the hybrid mode of science parks as industrial hubs and innovation centers in China, which other literature fails to elaborate this important distinction from other countries. Third, our research differentiates the short-term and long-term effects of firm entry on the growth of national science parks by studying the second and third venture stages of Z Park. We find that new entrants' contribution to TFP growth changes over time, reconciling the results obtained by existing studies. These findings have significant practical implications for policymakers and practitioners in the fields of innovation and entrepreneurship studies.

The rest of the paper is organized as follows: the second section introduces the method of the decomposition of productivity and size growth; the third section gives the description over data source and sample; the fourth section presents the empirical results and analysis of the effect of firm entry on TFP and output growth inside the science park; the fifth section provides the robust analysis; the sixth section ends with the conclusions and policy implications.

2 Method

This paper utilizes the decomposition method to measure the impact of firm entry on the productivity and size growth of a science park, respectively. First, the DOP decomposition method (Melitz and Polanec, 2015) is choosen over the BHC (Baily, Hulten, and Campbell, 1992), GR (Griliches and Regev, 1995), and FHK (Foster, Haltiwanger, and Krizan, 2001) decomposition method due to its its more accurate assessment of entry and exit effects over a long time span. Similarly, the study adopts the growth decomposition method of export size proposed by Eaton, Eslava, Kugler, and Tybout (2007) (referred to as the EEKT decomposition method) after making slight modifications, providing a clear rationale for this research context.

2.1 Decomposition of productivity growth

In this section, we first measure productivity using Total Factor Productivity (TFP). Then, we choose a proper decomposition method to evaluate the impact of firm entry on the TFP growth of a science park.

First, TFP is measured by the Solow residual, which is estimated from the Cobb-Douglas production function. Assume that the production function of the firms of a science park is

$$\ln y_{it} = \alpha_0 + \alpha_1 \ln k_{it} + \alpha_2 \ln l_{it}^h + \alpha_3 \ln l_{it}^l + \delta_i + \varepsilon_{it} \quad (1)$$

where y_{it}, k_{it}, l_{it}^h and l_{it}^l are the total output, fixed capital input, high-skilled (bachelor degree and above) and low-skilled (below bachelor degree) labour input of the i th firm in a science park in the period t, δ_i is the firm's individual fixed effects, and ε_{it} is a random error term. Total number of employees employed by the firm $l_{it} = l_{it}^h + l_{it}^l$.

Denote the logarithmic TFP at the firm level as $\gamma_{it} = \delta_i + \varepsilon_{it}$, and use the fixed effects model to estimate the above model to obtain the estimated value of γ_{it}. We obtain the TFP of a science park by summing up the product of γ_{it} and ω_{it} at the firm level.

$$\gamma_t = \sum_i \omega_{it} \gamma_{it} \quad (2)$$

where the weight $\omega_{it} = l_{it} \big/ \sum_i l_{it}$.

Enterprises with distinct status contribute variably to TFP growth. Firms are classified into three categories based on their status: new firms, incumbent firms, and exiting firms in this paper. Noting that the time interval is d ($d \geq 1$) years. If firm i is in a science park in the period t (i.e., it appears in the firm-level panel database) but not in a science park in period $t-d$ (i.e., it does not appear in the firm-level panel database), it is defined as a new firm in period t. If firm i is in a science park in period $t-d$, but not in the park in period t and subsequent periods, firm i is classified as an exiting firm in period t. All remaining firms are considered as incumbent firms. According to this definition, in period t, firms can be classified into incumbent firms and new entrants, while in period $t-d$, there are only incumbent firms and exiting firms.

Then, we distinguish different firms' respective impacts by decomposition methods. Literature has four different decomposition methods: the BHC, GR, FHK, and DOP methods. The BHC method decomposes TFP growth into a firm's productivity change (within-group effect) and market share change (between-group effect). Specifically, $\Delta\gamma_t$ is decomposed as (Baily, Hulten, and Campbell, 1992)

$$\Delta\gamma_t = \sum_{i\in C} \omega_{it-d} \Delta\gamma_{it} + \sum_{i\in C} \Delta\omega_{it}\gamma_{it} + \sum_{i\in N} \omega_{it}\gamma_{it} - \sum_{i\in X} \omega_{it-d}\gamma_{it-d} \quad (3)$$

where N, C, X denote new firms, incumbent firms and exiting firms respectively.

The first term $\sum_{i\in C} \omega_{it-d}\Delta\gamma_{it}$ in equation (3), named within-group effect, represents a within firm component based on the firm-level productivity change in period t, weighted by labor shares in period $t-d$. The second term $\sum_{i\in C} \Delta\omega_{it}\gamma_{it}$, named between-group effect, represents a between firm component that reflects changing labor shares, weighted by firm-level productivity. The sum of term (1) and term (2) measures the productivity change of incumbent firms. The third term $\sum_{i\in N} \omega_{it}\gamma_{it}$ is the contribution of new firms to productivity growth, called the entry effect. The last term $-\sum_{i\in X} \omega_{it-d}\gamma_{it-d}$ is the contribution of exit firms to productivity growth, measuring the exit effect.

The disadvantage of the BHC decomposition method is that, theoretically, the entry effect is always positive since a firm's productivity is positive ($\gamma_{it} > 0$). Similarly, the effect for exiting firms is always negative. However, in reality, the entry effect is positive only when the productivity of new entrants exceeds the overall productivity level of a science park. Similarly, the exit effect is not necessarily harmful when the productivity of exiting firms is below the overall productivity level.

The GR decomposition method (Griliches and Regev, 1995) addresses this issue by separating the influence of overall productivity, thereby decomposing productivity changes as

$$\Delta\gamma_t = \sum_{i\in C}\bar{\omega}_i\Delta\gamma_{it} + \sum_{i\in C}\Delta\omega_{it}(\bar{\gamma}_i - \bar{\gamma}) + \sum_{i\in N}\omega_{it}(\gamma_{it} - \bar{\gamma}) - \sum_{i\in X}\omega_{it-d}(\gamma_{it-d} - \bar{\gamma}) \qquad (4)$$

where $\bar{\gamma}_i$ and $\bar{\gamma}$ are the average of productivity for the i th firm and a science park in a specific period respectively, i.e. $\bar{\gamma}_i = (\gamma_{i,t-1} + \gamma_{it})/2$, $\bar{\gamma} = (\gamma_{t-1} + \gamma_t)/2$; Similarly, $\bar{\omega}_i$ is the average of market share for the i th firm in period t, i.e. $\bar{\omega}_i = (\omega_{i,t-1} + \omega_{it})/2$. From the above equation, we know that only when the productivity of new entrants is higher (or lower) than the average productivity in the period t of a science park, will they boost (or pull down) the productivity of a science park. Similarly, exiting firms will pull down (or boost) the productivity of Z Park only when their productivity is higher (or lower) than the average productivity of a science park.

The FHK decomposition method (Foster, Haltiwanger, and Krizan, 2001) makes two adjustments to the GR decomposition method. First, a new entrant compares its productivity with the initial productivity of a science park before its entry instead of the average productivity of before and after its entry. Second, it separates the cross-effects $\sum_{i\in C}\Delta\omega_{it}\Delta\gamma_{it}$ from the within-group and between-group effects though it is statistically tiny. Then, the productivity growth is decomposed into within-group , between-group, cross, entry, and exit effects. That is

$$\begin{aligned}\Delta\gamma_t &= \sum_{i\in C}\omega_{it-d}\Delta\gamma_{it} + \sum_{i\in C}\Delta\omega_{it}(\gamma_{it-d} - \gamma_{t-d}) + \sum_{i\in C}\Delta\omega_{it}\Delta\gamma_{it} \\ &+ \sum_{i\in N}\omega_{it}(\gamma_{it} - \gamma_{t-d}) - \sum_{i\in X}\omega_{it-d}(\gamma_{it-d} - \gamma_{t-d})\end{aligned} \qquad (5)$$

From equation (5), we can notice that a new entrant will raise (or pull down) the productivity of a science park if its productivity is higher (or lower) than the initial productivity of the park before its entry. However, it ignores the dynamic change of incumbent firm's productivity after new firms enter.

The DOP decomposition method has unique advantages by considering the heterogeneity of inter-period firm composition. TFP_t in period t is the weighted sum of the TFP of the incumbent firm and the entering firm, and TFP_{t-1} in period $t-1$ is the weighted sum of the TFP of the incumbent firm and the exiting firm TFP, i.e.

$$\gamma_t = \gamma_{Ct}\sum_{i\in C}\omega_{it} + \gamma_{Nt}\sum_{i\in N}\omega_{it} = \bar{\gamma}_{Ct} + \sum_{i\in C}(s_{it} - \bar{s}_{Ct})(\gamma_{it} - \bar{\gamma}_{Ct}) + \sum_{i\in N}\omega_{it}(\gamma_{Nt} - \gamma_{Ct}) \qquad (6)$$

$$\begin{aligned}\gamma_{t-d} &= \gamma_{C,t-d}\sum_{i\in C}\omega_{i,t-d} + \gamma_{X,t-d}\sum_{i\in X}\omega_{i,t-d} = \bar{\gamma}_{Ct-d} + \sum_{i\in C}(s_{i,t-d} - \bar{s}_{Ct-d})(\gamma_{i,t-d} - \bar{\gamma}_{C,t-d}) \\ &+ \sum_{i\in X}\omega_{i,t-d}(\gamma_{X,t-d} - \gamma_{C,t-d})\end{aligned} \qquad (7)$$

Let $J \in \{C, N, X\}$, then $\gamma_{Jt} = \sum_{i\in J}s_{it}\gamma_{it}$, $s_{iJt} = \omega_{it}/\omega_{Jt}$, $\omega_{Jt} = \sum_{i\in J}\omega_{it}$. $\bar{s}_{Ct} = (1/n_{Ct})\sum_{i\in C}s_{it}$, $\bar{\gamma}_{Ct} = (1/n_{Ct})\sum_{i\in C}\gamma_{it}$, n_{Ct} is the number of the incumbent firms, $\omega_{Ct} + \omega_{Nt} = 1$, $\omega_{C,t-d} + \omega_{X,t-d} = 1$. Then the productivity change from period $t-d$ to t is decomposed into within-group effects, between-group effects, entry effects and exit effects

$$\begin{aligned}\Delta\gamma_t &= \Delta\bar{\gamma}_{Ct} + \Delta\sum_{i\in C}(s_{it} - \bar{s}_{Ct})(\gamma_{it} - \bar{\gamma}_{Ct}) \\ &+ \omega_{Nt}(\gamma_{Nt} - \gamma_{Ct}) - \omega_{X,t-d}(\gamma_{X,t-d} - \gamma_{C,t-d})\end{aligned} \qquad (8)$$

As seen from equation (8), $\omega_{Nt}(\gamma_{Nt} - \gamma_{Ct})$ reflects the contribution of entering firms to aggregate productivity. The productivity contribution of entering firms is positive only if the productivity of new entrants is higher than the productivity of the incumbent firms γ_{Ct}.

Regarding the entry effect, the GR, FHK, and DOP methods adopt different productivity benchmarks: the GR method relies on the average productivity, FHK the initial productivity, and DOP the endpoint productivity. The DOP method overcomes the chronological effect of firm productivity and provides a more accurate assessment of entry and exit effects compared to the other two methods. If the growth period is short, such as one year, the results from these three methods will be approximately the same. However, the DOP decomposition of entry effects tends to be more precise for a more extended growth period. For example, if the productivity of incumbent firms grows by 100% between 2005 and 2015, and the TFP of new firms during this period is slightly lower than that of the incumbents in 2015, the overall productivity growth rate of a science park should be less than

100%. In this case, the DOP decomposition would show a negative entry effect, but the GR and FHK methods would indicate a positive one.

When we focus on the productivity growth mechanism of new firms, the DOP decomposition allows us to dissect the growth contribution of new entrants. This breakdown reveals the significant and intriguing role of the post-entry learning effect of firms at different years of entry relative to the incumbent firms. This effect, a crucial and engaging aspect of the growth dynamics, keeps us involved in understanding the growth of a science park.

$$\omega_{Nt}(\gamma_{Nt}-\gamma_{Ct})=\omega_{Nt}\sum_{\bar{t}=t-d+1}^{t}(\gamma_{i,\bar{t}}-\gamma_{C\bar{t}})+\omega_{Nt}\sum_{\bar{t}=t-d+1}^{t}\sum_{t'=\bar{t}}^{t}\Delta(\gamma_{i,t'}-\gamma_{Ct'}) \quad (9)$$

where $\bar{t}$ ($t-d<\bar{t}\le t$) denotes the entry year of new firms, the first term represents the selective effect, and the second term represents the learning effect.

2.2 Decomposition of size growth

We use business revenue to measure the size of firms in a science park. Let $y_{i,t}$ refer to the business revenue of the firm i in the t period, and Y_t the total revenue of this park in the t period. As defined in the previous section, high-tech firms in period t consist of incumbent firms and new entrants, while high-tech firms in period $t-d$ consist of incumbent and exiting firms. Let

$$Y_t=\sum_{i\in N}y_{it}+\sum_{i\in C}y_{it} \quad (10)$$

$$Y_{t-d}=\sum_{i\in C}y_{it-d}+\sum_{i\in X}y_{it-d} \quad (11)$$

In the EEKT decomposition method (Eaton, Eslava, Kugler, and Tybout, 2007), the denominator of the aggregated growth rate is equal to the average of the revenue in the current and the previous period, denoted by $(Y_{t-d}+Y_t)/2$. It is crucial to note that, in order to be consistent with the growth accounting convention and the calculation of the aggregate productivity growth, this paper uses the revenue in the prior period as the denominator for the aggregate growth rate, denoted by Y_{t-d}. Ultimately, the revenue growth rate of a science park for the period t can be decomposed into

$$\frac{Y_t-Y_{t-d}}{Y_{t-d}}=\frac{\sum_{i\in N}y_{it}}{Y_{t-d}}+\frac{\sum_{i\in C}(y_{it}-y_{it-d})}{\sum_{i\in C}y_{it-d}}\frac{\sum_{i\in C}y_{it-d}}{Y_{t-d}}-\frac{\sum_{i\in X}y_{it-d}}{Y_{t-d}} \quad (12)$$

where the right-hand side of the above equation denotes the contribution of new entrants, incumbents, and exiting firms, respectively, to the growth rate of revenues in the science park.

Equations (10), (11), and (12) reveal the dynamic and complex nature of the revenue growth in the science park. The revenue increment of the incumbent firms between period $t-d$ and period t is counted into the total increment of the science park. The gross revenue of new entrants in period t is directly added to the total incremental revenue of the science park. The gross revenue of exiting firms in period $t-d$ is deducted from the total incremental revenue of the science park. Similarly, the role of new firms in the revenue growth of the science park is different at various stages after their entry. In the first entry year, the total revenue of a new firm is counted in the total incremental revenue of the science park. However, the real test comes one year later, when a survived new firm transforms into an incumbent. Therefore, its incremental revenue is added to the total incremental revenue of the science park. Unless it doubles its growth, its contribution to the revenue growth of the park will decline after the year of entry compared to the year of entry.

The revenue growth contribution from new entrants can be broken down into the level effect in the year of entry and the subsequent growth effect after their entry. i.e.

$$\frac{\sum_{i\in N} y_{i,t}}{Y_{t-d}} = \frac{\sum_{i\in N}\sum_{\bar{t}=t-d+1}^{t} y_{i,\bar{t}}}{Y_{t-d}} + \frac{\sum_{i\in N}\sum_{\bar{t}=t-d+1}^{t}\sum_{t'=\bar{t}}^{t} \Delta y_{i,t'}}{Y_{t-d}} \quad (13)$$

where $\bar{t}$ ($t-d<\bar{t}\le t$) denotes the entry year of new firms as before. Equations (9) and (13) demonstrate that the entry of a new firm affects productivity and size growth in distinct ways.

3 Data

3.1 Data source

This paper uses Z Park in Beijing as an example of a Chinese national science park. The predecessor of Z Park was the Beijing Experimental Zone for High-tech Industries, which was established in 1988. After over 30 years of development, it is currently the largest science park in China. The data used in this paper is the firm-level data on Z Park, a comprehensive dataset covering the period from 2005 to 2015, and all firms in the park must satisfy the high-tech identification standards of the national science park. Whether a firm can enter Z Park is evaluated after its application, and the assessment criteria include indexes such as the proportion of personnel engaged in R&D activities, the intensity of R&D investment, and the proportion of high-tech products. This panel dataset comprises 251,633 observations of 36,406 firms of various sizes and industries.

Z Park has advanced through the second and the third venture stages during the sample period. The number of firms in the sample each year fluctuates between 15,000 and 20,000 (Table 1). In 2015, Z Park's total business revenue reached 4.1 trillion yuan, a substantial 8.4 times higher than in 2005, with an annual average growth rate of 23.9%. However, the growth of per capita business revenue is much slower than the growth of total business revenue. Specifically, per capita business revenue increased from 0.71 million yuan in 2005 to 1.79 million yuan in 2015, with an average annual growth rate of 9.8%, less than half the total business revenue growth rate.

3.2 Descriptive statistics

Table 1 shows the dynamic change of firm status from 2006 to 2015. From 2006 to 2008, the entry rate of new firms is much larger than their revenue share. That is, new entrants' revenue size is more minor than incumbent enterprises. 2009 witnesses an important turning point. In contrast, the revenue share of new firms after 2009 is notably higher except in 2010, while the proportion of new firms after 2009 does not significantly increase. This can be attributed to the amendment of high-tech identification standards of the national science park in 2008, which lowered the requirement for R&D investment for large size firms. As a result, large enterprises with revenues exceeding 50 million yuan are more likely to enter Z Park. Additionally, the number of exiting firms is similar to new firms, but their revenue share is much lower, hovering around 3 percent across years.

Table 1 Entry and exit rates of the firms in Z Park

Year	New firms (%)		Exiting firms (%)		Number of the firms in the sample	Total business revenue (trillion)	Per capital business revenue (million)
	entry rate	Revenue share	exit rate	Revenue share			
2006	23.2	9.9	13.9	3.6	15955	0.7	0.71
2007	18.8	7.8	15.1	2.3	18148	0.9	0.85

2008	11.6	4.2	10.1	2.4	19254	1.0	1.00
2009	8.9	15.8	16.3	1.3	18447	1.3	1.09
2010	3.8	2.3	10.7	2.3	16953	1.6	1.22
2011	5.0	11.5	9.2	2.3	15720	2.0	1.38
2012	8.9	18.5	9.5	2.3	15026	2.5	1.42
2013	23.3	17.6	20.6	5.7	14929	3.0	1.58
2014	17.3	9.3	16.3	2.2	15455	3.6	1.61
2015	26.3	11.0	21.4	2.7	15645	4.1	1.79
Average	14.7	10.8	14.3	2.7	16566	—	—

4 Empirical results

4.1 The impact firm entry on the TFP growth in Z Park

Table 2 presents the results of the DOP decomposition of TFP growth in Z Park by firm identity after calculating TFP by equation (1), where the estimated coefficients of capital, low-skilled labor, and high-skilled labor are 0.150, 0.344, and 0.431, respectively. It is important to note that the TFP growth rate of Z Park was positive for most years from 2006 to 2015 except for 2015, showing the enhanced firm efficiency year by year. The average contribution of new firms to annual TFP growth in the entry year is -27.9%, which suggests that the TFP of new entrants upon entering Z Park is lower than that of incumbent firms, pulling down the overall TFP growth of Z Park.

However, the negative effect on TFP growth of new entrants was significantly reduced after the implementation of a new identification standard for high-tech enterprises in 2008, which particularly benefits large-size enterprises. Specific years even witness the positive impact of firm entry on TFP growth rate, such as 2009, 2011, 2014, and 2015. Besides, incumbent firms mainly contributed to TFP growth in Z Park, whose growth can explain the 96.9% average TFP growth rate and 65.2% ten-year cumulative TFP growth rate. The average contribution of exiting firms to annual TFP growth in the exit year is 31%, which indicates inefficient firms had been shut down due to the crucial role of market competition.

Table 2 Contribution of firm entry to the TFP growth in Z Park (Unit: %)

Year	TFP growth rate	Contribution rate of firms			Growth rate of firms		
		New	Exiting	Incumbent	New	Exiting	Incumbent
2006	19.4	-47.5	35.4	112.1	-9.22	6.87	21.75
2007	25.0	-25.2	24.9	100.3	-6.30	6.23	25.08
2008	4.5	-154.6	64.8	189.8	-6.96	2.92	8.54
2009	16.4	31.6	40.9	27.5	5.18	6.71	4.51
2010	14.6	-11.4	19.5	91.9	-1.66	2.85	13.42
2011	9.2	8.5	15.6	75.9	0.78	1.44	6.98
2012	6.3	-29.4	30.2	99.2	-1.85	1.90	6.25
2013	5.5	-28.2	38.2	89.9	-1.55	2.10	4.94
2014	10.4	4.3	29.7	66.0	0.45	3.09	6.86

2015	-1.0	999.2	-14.8	-884.3	9.99	-0.15	-8.84
Yearly average	11.0	-27.9	31.0	96.9	-3.07	3.41	10.66
Ten-year cumulative	110.3	5.4	29.4	65.2	5.96	32.43	71.92

Note: The sum of column (3), (4), and (5) is equal to 100%, and the sum of column (6), (7), and (8) is equal to column (2). TFP growth for incumbent firms is a combination of within-group effects, between-group effects and cross terms; for "yearly average", the average contribution of the firms of the three types is calculated for each year before their respective contribution rates are calculated.

To assess the medium- and long-term dynamic effects of new entrants after their entry, we further estimate the impact on TFP growth over an extended time horizon. This analysis will illustrate the selective effect and learning effect as described in equation (9). Table 3 presents the estimated impact of firm entry in different years on the TFP growth within Z Park, using 2005 as the base year. The last row of Table 3 shows the cumulative contribution of new entrants to overall TFP growth, which shifts from -47.5% to a positive value over time. Initially, due to the preponderance of the negative selection effect, a new entrant's TFP is lower than that of incumbent firms. However, the learning effect is crucial in narrowing the TFP gap between new and incumbent firms. For most years, firms that enter Z Park later tend to have a lesser contribution to TFP growth. For example, as indicated in each column, a firm that entered Z Park in 2008 had a contribution of -11.4% to TFP growth, negatively affecting the overall growth that year. This demonstrates that the negative selection effect outweighs the positive learning effect during this period. Conversely, a firm that entered in 2006 showed a positive contribution of 0.7% to the TFP growth, indicating that the positive learning effect has begun to surpass the negative selection effect. From 2006 to 2015, the cumulative contribution of new firms to TFP growth is 5.4%.

Table 3 Dynamic trends in the contribution of firm entry to TFP growth in the science park (Unit: %; with 2005 as the base year)

Current year / Year of entry	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
2006	-47.5	0.0	0.7	3.1	4.4	3.8	2.3	0.9	0.2	0.4
2007		-13.8	-3.7	-0.4	0.8	1.0	0.6	0.2	0.5	0.5
2008			-11.4	-3.2	-2.0	-0.8	-0.7	-0.2	-0.3	0.0
2009				8.5	8.7	4.7	4.2	3.4	4.1	4.2
2010					-1.1	-0.3	0.1	0.0	-0.2	-0.2
2011						1.9	3.6	1.7	1.3	1.1
2012							0.2	0.2	1.4	1.4
2013								1.4	1.7	3.7
2014									1.7	0.3
2015										-5.9

Cumulative	-47.5	-13.8	-14.5	8.1	10.7	10.4	10.3	7.7	10.2	5.4

Note: The first row indicates the contribution rage of new firms entering the science park in 2006 to the cumulative TFP growth of the science park in 2006, ..., 2015 with 2005 as the base year, and the indications of the other rows are similar; the last row of "Cumulative" refers to the contribution of new firms to the cumulative TFP growth of the time periods with 2005 as the base year.

The estimated short-term contribution of firm entry to TFP growth in Z Park is lower than that of national industrial firms, while the long-term contribution is slightly higher. For instance, Dai (2021) finds that the average short-term contribution of firm entry to TFP growth for two consecutive years (1999–2007) is -4.5%, while the cumulative contributions for 1999–2007, as measured by Yang (2015) and Wu (2016) are 3.5% and negative, respectively. These suggest that high-tech firms within Z Park, with their remarkable learning capabilities, are able to catch up with incumbents more effectively than general industrial firms.

To comprehensively examine the dynamic TFP growth trend of new firms after their entry, we further conduct a regression analysis using equation (14) to assess the contribution of new firms to TFP growth or TFP level in Z Park relative to incumbents.

$$\ln Z_{it} = \alpha_0 + \sum_{d=0}^{D} \alpha_d Dum_{i,t+d} + \sum_{k=1}^{K} \gamma_k X_{i,k,t} + u_i + \varepsilon_{it} \qquad (14)$$

where Z_{it} denotes TFP growth or TFP level of firm i in the t th period. We also use it to denote revenue growth rate or revenue level in the next section; $Dum_{i,t+d}$ denotes the dummy variable of the firm i entering Z Park d years after the t th year, and if it has entered d years, the variable is taken as 1, otherwise taken as 0; the coefficient of the dummy variable denotes growth rate or level of a new firm relative to an incumbent firm in Z Park d years after entry; the control variable $X_{i,k,t}$ denotes other characteristics of the firm i, including the logarithm of a firm employment size, the logarithm of a firm per capita capital, and industry-year cross- term fixed effects; u_i is a firm individual fixed effects, etc.

Table 4 displays the regression results of equation (14). Columns (1) and (2) illustrate the dynamic trends of TFP growth and TFP levels for new firms compared to incumbent firms after entering Z Park. From Column (2), we see that the TFP level of new firms at the time of entry is significantly lower than that of incumbent firms, with a coefficient of -0.431. Column (1) indicates that in the first year after entering Z Park, the TFP growth rate of new firms is 0.460 higher than that of incumbents. Consequently, the TFP gap between new and established firms narrows over time. However, the efficiency advantage of new firms over incumbents declines thereafter, and by the third year, the efficiency of new firms converges with that of incumbent firms. By the fifth year, new firms' TFP has slightly exceeded that of incumbents, reflecting the cumulative learning effect in Z Park.

This finding is consistent with the research conducted by Brandt et al. (2012), which observed that new firms start with lower TFP than incumbent firms but experience faster growth in the subsequent years, based on a study of national industrial firms from 1998 to 2007. However, our research provides a more detailed illustration of growth dynamic in TFP, indicating that the faster growth of new firms over established firms cannot last indefinitely, as they eventually transition to the status of incumbent enterprises a few years later.

Table 4 TFP and revenue growth trend of new firms relative to incumbent firms after entering Z Park

	(1)	(2)	(3)	(4)
	TFP growth	TFP level	Revenue growth	Revenue level
$T+0$		-0.431^{***}		-0.469^{***}

(current year)		(0.034)		(0.033)
$T+1$	0.460 ***	-0.150 ***	0.663***	-0.175***
	(0.034)	(0.030)	(0.033)	(0.029)
$T+2$	0.098 ***	-0.093***	0.202***	-0.104***
	(0.030)	(0.027)	(0.030)	(0.027)
$T+3$	0.013	-0.048**	0.058**	-0.051**
	(0.027)	(0.024)	(0.026)	(0.024)
$T+4$	0.026	-0.012	0.048**	-0.014
	(0.024)	(0.021)	(0.024)	(0.021)
$T+5\sim8$	-0.003	0.025*	-0.008	0.027*
	(0.015)	(0.014)	(0.015)	(0.014)
employment size	-0.085***	0.091 ***	0.222***	0.846***
	(0.008)	(0.007)	(0.008)	(0.007)
per capita capital	-0.068 ***	-0.031***	0.004	0.155***
	(0.005)	(0.005)	(0.005)	(0.005)
Industry-year fixed effect	Yes	Yes	Yes	Yes
individual fixed effect	Yes	Yes	Yes	Yes
sample size	125740	150545	126742	150921
R^2	0.230	0.765	0.278	0.898

Note: *, **, *** denote the significant level at 10 percent, 5 percent and 1 percent, respectively; The numbers in the parentheses are robust standard deviations.

4.2 The impact firm entry on the revenue growth in Z Park

Table 5 presents the results of the EEKT decomposition of revenue growth in Z Park by firm status. From 2006 to 2015, the total revenue generated by new entrants constituted a small proportion-only 10.8%- of Z Park's overall revenue (see Table 1). However, new firms contributed significantly to the annual revenue growth rate, accounting for as much as 56.3% (see Table 5), which is even slightly higher than the contribution from established firms. In contrast, exiting firms had an average negative contribution of -11.4%. Thus, both new entrants and incumbent firms play crucial roles in driving the revenue growth of Z Park.

Except for 2010, the contribution of new firms has substantially increased each year since 2008. This growth may be attributed to the implementation of the new entry criteria for large-size firms introduced in 2008. It is worth noting that when a new firm transitions to an established firm, its contribution to growth tends to decline unless it significantly boosts its yearly growth. Furthermore, the impact of firm entry on the revenue growth in Z Park is greater than that at the national level, with a contribution rate of 46.3% from 1998 to 2007, as found by Li and Jiang (2015).

Table 5 Contribution of firm entry to the revenue growth in Z Park (Unit: %)

Year	revenue growth rate	Contribution rate of firms			Growth rate of firms		
		New	Exiting	Incumbent	New	Exiting	Incumbent
2006	38.3	35.7	-9.3	73.6	13.67	-3.56	28.19
2007	34.0	30.7	-6.7	76.0	10.44	-2.28	25.84
2008	13.1	36.6	-18.4	81.8	4.79	-2.41	10.72
2009	27.2	73.9	-4.9	31.0	20.10	-1.33	8.43
2010	22.6	12.4	-10.4	98.0	2.80	-2.35	22.15
2011	23.2	61.0	-9.8	48.8	14.15	-2.27	11.32
2012	27.4	86.0	-8.5	22.5	23.56	-2.33	6.17
2013	21.9	98.3	-26.1	27.9	21.53	-5.72	6.11
2014	18.2	60.2	-12.0	51.8	10.96	-2.18	9.43
2015	13.2	94.9	-20.5	25.7	12.53	-2.71	3.39
Yearly average	23.9	56.3	-11.4	55.1	13.46	-2.72	13.17
Ten-year cumulative	736.8	83.1	-3.2	20.1	612.28	-23.58	148.10

Note: The sum of column (3), (4), and (5) is equal to 100%, and the sum of column (6), (7), and (8) is equal to column (2). for "yearly average", the average contribution of the firms of the three types is calculated for each year before their respective contribution rates are calculated.

Table 6 presents the estimated contribution of new firm entries to the current revenue growth of Z Park over various years. New firms robustly drive Z Park's revenue growth in their entry year, contributing, on average, 56.3% to annual revenue growth in the entry year. However, this contribution declines in subsequent years, decreasing to only 12.1%, 5.6%, and 3.9% in the first, second, and third year, respectively. This trend indicates that the level effect is more prominent than the growth effect, as described in equation (14). The reduction in growth is primarily attributed to a slowdown in the growth rate of existing firms and some firms exiting the market.

The last column of Table 6 outlines the cumulative growth contribution of new firms based on their entry year, indicating that they contributed 83.1% to total revenue growth between 2005 and 2015. This figure is 16.8% higher than the annual revenue growth of Z Park, highlighting the impact of new firms' learning capability.

Table 6 Dynamic trends in the contribution of firm entry to revenue growth in the science park (Unit: %)

Current year / Year of	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Cumulative

entry											
2006	35.7	23.7	14.3	3.9	11.7	4.4	-4.2	-0.9	-0.2	-0.3	4.6
2007		30.7	19.4	7.0	9.5	1.6	-1.3	3.1	3.0	1.4	4.1
2008			36.6	6.6	1.5	-0.9	1.8	1.7	0.8	3.7	2.6
2009				73.9	32.4	10.2	0.9	3.4	15.6	21.2	14.0
2010					12.4	7.6	1.0	1.6	0.0	-5.0	0.9
2011						61.0	14.9	6.6	8.4	-0.9	9.1
2012							86.0	8.3	12.9	5.1	12.4
2013								98.3	9.7	-2.8	13.8
2014									60.2	3.2	9.4
2015										94.9	12.1
Cumulative											83.1

Note: The first row indicates the contribution rate of new firms entering the science park in 2006 to the revenue growth of the science park in 2006, ..., 2015, and the indications of the other rows are similar. The last column "Cumulative" refers to the contribution of new firms in each entry year to the cumulative revenue growth in the period between 2005 and 2015.

In addition to our comprehensive examination of dynamic trend in TFP growth trend for new firms' following their entry, we also conduct a regression analysis using equation (14) to evaluate the impact of new firms on the dynamic changes in revenue growth in Z Park compared to incumbents. Columns (3) and (4) in Table 4 displays the regression results, which employs either revenue growth rate or revenue level as a measurement of Z_{it}.

Column (4) in Table 4 illustrates the trend of the revenue level of new firms compared to established ones. We observe that, in year zero, the revenue of new firms is significantly smaller than that of incumbent firms, with a coefficient of -0.469. This finding indicates that the entry effect is always positive as long as a firm's revenue exceeds zero. Additionally, this entry effect is substantial, as the revenue levels of new firms in their initial year are calculated in the total revenue growth of Z Park.

Column (3) in Table 4 shows the dynamic trend of revenue growth of new firms in relation to incumbent firms after their entry. On average, the revenue growth rate of new firms is 0.663 higher than that of incumbent firms in the first year. As a result, the revenue gap between new and established firms narrows over time. However, this relative growth advantage diminishes and even disappears. By the fifth year, new firms' revenue levels slightly surpass that of incumbents, similar to findings on TFP. This observation aligns with previous research by Li and Jiang (2015), which indicates that new firms in the science park are smaller than incumbent firms in the year of entry but experience faster relative growth thereafter, based on their study of national industrial firms from 1999 to 2007.

In summary, new firms entering the science park exhibit lower TFP and revenue sizes, indicating a negative selection effect. However, their learning capabilities allow them to catch up with and exceed established firms eventually. The learning effect for new firms after entry occurs for two main reasons. On the supply side, new firms build experience and abilities through a "learning by doing" mechanism in production and management. As they accumulate knowledge from internal production management practices, they also benefit from knowledge spillovers resulting from industrial agglomeration and the externality of human capital within the science park. Thus, it will take time for new firms to increase output and TFP. On the demand side, market demand for new firms is inherently uncertain. Their growth relies on building product reputation, effective marketing, and fostering repeated interactions between producers and consumers (Foster, Haltiwanger, and Syverson, 2016).

5 Robustness Tests

5.1 Different TFP growth decomposition methods

To evaluate the reliability of decomposition results obtained by the DOP method, we apply the GR and FHK methods to decompose the TFP growth of Z Park, illustrated in Table 7. Notably, there are significant differences between results obtained from GR, FHK, and DOP method for both yearly and cumulative TFP growth from 2006 to 2015.

The estimated contribution of new firms to cumulative TFP growth varies by method: 5.4% according to the DOP method, 36% based on the GR method, and 70.4% by the FHK method. These discrepancies arise from the differing measures of the overall TFP level that each method uses to assess the entry effect. Specifically, the DOP method relies on the productivity of incumbent firms at the end of the period, while the FHK method uses overall productivity at the beginning of the period. The GR method takes the average productivity at the beginning and end of the period. Although the differences between these methods are relatively minor over a one-year interval, they become more pronounced as the time interval lengthens. All three methods indicate that the contribution of new firms to overall TFP growth is negative in the year they enter. However, the cumulative contribution turns positive because of the learning effect, which validates the robustness of the conclusions derived from the DOP decomposition method.

Table 7 Decomposition of TFP growth of the science park using different decomposition methods (%)

	Yearly growth			Cumulative growth		
	New firms	Exiting firms	Incumbent firms	New firms	Exiting firms	Incumbent firms
GR	-18.3	32.4	85.9	36	36.2	27.8
FHK	-12.5	30.2	82.3	70.4	17.2	12.4
DOP	-27.9	31.0	96.9	5.4	29.4	65.2

5.2 Different size and productivity indicators

This paper utilizes alternative indicators to measure productivity and size, aiming to further validate the robustness of the estimations. In Table 8, when we use per capita revenue as the efficiency indicator, the decomposition reveals that firm entry positively influences annual per capita revenue growth. This finding contrasts with the negative entry effect of entry on TFP growth, which may be due to new firms having a higher per capita revenue compared to incumbent firms. Additionally, new firms' contribution to the cumulative growth of per capita revenue is higher, driven by the learning effect.

The analysis of various size indicators, including profit, R&D investment, the number of patents granted, and employment size (specially for those with undergraduate-level education and above), shows that entry of new firms substantially contributes to both annual and cumulative size growth of Z Park. This is consistent with the revenue measurements as a size indicator. Notably, nearly 100% employment growth can be attributed to firm entry. Furthermore, the learning effect of new firm is evident when comparing the differences between the cumulative and yearly growth contributions of these size indicators, further validating the robustness of the previous findings.

Table 8 Decomposition of growth of various productivity and size of the science park (%)

	Yearly growth			Cumulative growth		
	New firms	Exiting firms	Incumbent firms	New firms	Exiting firms	Incumbent firms
(a) Productivity indicators:						
Per capita revenue	17.1	2.4	80.5	28	11.8	60.2
(b)Size indicators:						
Revenue	56.3	-11.4	55.1	83.1	-3.2	20.1
Profit	40.9	-6.4	65.5	72.1	-2.4	30.3
R&D investment	79.6	-19.9	40.3	97.4	-18.2	20.8
No. of invention patents granted	40.3	-17.5	77.2	56.9	-3.5	46.6
Employment size	99.9	-27.6	27.6	97.1	-16.4	19.3
Undergraduate and above	82.2	-24.3	42.1	88.8	-14.3	25.5

5.3 Industry differences

This section aims to determine whether the previous findings hold true across industries. Table 9 presents new firms' contributions to TFP and revenue growth across 15 two-digit industries.

In terms of TFP growth contributions, the selection effect of firm entry is negative, meaning that new firms initially have lower TFP levels than incumbent firms, with two exceptions: the telecommunications, radio and television broadcasting, satellite transmission services industry, and the research and experimental development industry. However, through the learning effect, new firms gradually close the gap, with approximately half of them eventually surpassing the incumbent firms. Overall, new firms yield the most significant impact in the telecommunications, radio and television broadcasting, and satellite transmission services industry, while their impact is lowest in the science and technology promotion and application services industry.

Regarding revenue growth contributions, the learning effect of new firms plays a crucial role. While new firms' entry rates and revenue shares are relatively low, their influence on revenue growth is significant across all industries. The most considerable contribution is observed in the computer and communication equipment manufacturing industry, and while the smallest is found in the pharmaceutical manufacturing industry. The differences in annual and cumulative revenue growth contributions indicate that all industries benefit from the learning effect of new firms, with the computer and communication equipment manufacturing industry reaping the greatest benefits, and the specialized equipment manufacturing industry gaining the least.

In conclusion, distinguishing between industries reinforces the general conclusion on the effect of firm entry on the growth of Z Park above. The variations observed across industries can be attributed to differences in cumulative technological capabilities, market opportunities, and specific demand characteristics inherent to each industry.

Table 9 Contribution of firm entry to TFP and revenue growth by industry

	Level percentage		Contribution to TFP growth		Contribution to Revenue growth	
	Entry	Average	Yearly	Cumula	Yearly	Cumul

	rate	percentage		tively		atively
Pharmaceutical manufacturing	10.8	4.0	-38.2	15.0	24.8	37.4
General equipment manufacturing	11.7	9.5	-19.3	-8.8	61.3	76.4
Special equipment manufacturing	10.4	7.3	-19.3	-9.1	65.8	66.2
Transport and aerospace equipment manufacturing	12.5	12.6	-6.1	24.4	54.7	93.2
Electrical machinery and equipment manufacturing	11.9	6.3	-21.8	-10.9	34.5	71.4
Computer and communications equipment manufacturing	6.5	3.2	-8.9	5.3	63.7	139.7
Instrument manufacturing	7.2	3.5	-15.1	-23.5	32.7	43.2
Telecommunications, radio and television broadcasting and satellite transmission services	10.1	10.0	23.8	35.9	53.3	87.6
Internet and related services	13.9	6.5	-43.3	10.5	22.8	65.8
Software and information technology services	13.4	4.0	-64.1	-24.9	30.7	50.8
Rental and business services	20.3	16.2	-15.9	20.0	48.1	81.6
Research and experimental development	12.4	10.9	4.0	-16.9	32.0	81.0
Professional and technical services	17.7	10.7	-33.1	13.1	44.7	91.6
Science and technology promotion and application services	17.0	6.5	-479.4	-205.7	29.4	71.6
Other industries	15.7	17.5	-8.5	17.8	70.2	87.7

Note: "Yearly growth" refers to growth in the current year relative to the previous year, and "cumulative growth" refers to cumulative growth over the period between 2005 and 2015.

6 Conclusions

This paper uses Z Park as an example to empirically analyze the dynamic impact of firm entry on the TFP and size growth of the science parks from 2005 and 2015. We reach the following key findings: First, although the TFP and revenue and levels of new firms entering the science park are initially lower than those of incumbent firms, the gap between the two narrows or even reverses. This is due to the higher growth rate of new firms compared to incumbents. Second, while the TFP level of newly established firms is lower than the overall level of Z Park in the year of entry, they initially have a negatively impact on TFP growth. However, their contribution to cumulative productivity growth becomes positive over time as they benefit from the learning process. Third, in contrast to their effect on TFP growth, new firms significantly boost the annual revenue growth of Z Park during their entry year. However, once they transition into incumbent firms, their annual contribution to revenue declines sharply, while their cumulative contribution increases slowly due to the learning effect. The robustness of our analysis, validated through various TFP decomposition methods, alternative productivity and size indicators, and across different industries, reinforces these conclusions, providing a solid foundation for further research and policy decisions.

The findings of this study support the need for the Chinese government to update innovation-related industrial policies based on the different stages of a firm's life cycle. First, the government must enhance the management process for identifying high-tech firms. Our study reveals that the selection effect for new firms within Z Park is relatively low, even lower than that for national industrial firms. Therefor, the government should evaluate potential applicants according to established high-tech firm identification standards, allowing only those that meet these criteria to gain entry. Second, new high-tech firms encounter significant technological and market risks during their early stages and typically undergo about a five-year learning process to catch up with incumbent firms. To help these firms navigate through the Death Valley, it is essential to implement systematic policies. These may include providing financial subsidies, tax exemptions, technological financing, talent policies, and market promotion efforts that enhance their innovation capabilities and resilience to market risks, ultimately accelerating their growth. Third, the government should promote a dynamic exit management mechanism. While the exit of firms may reduce the revenue size of Z Park, it can also improve overall productivity. Therefore, the government should phase out firms that no longer meet high-tech standards, and redirect scarce public resources towards new or high-growth firms.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, author-ship, and/or publication of this article.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Funding

This research was funded by National Social Science Fund of China (22BJY123).

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