*Science and Public Policy*, 46(2), 2019, 232–243
doi: 10.1093/scipol/scy053
Advance Access Publication Date: 10 August 2018
Article

# Dynamic evaluation of the technological innovation efficiency of China's industrial enterprises

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**Abstract**

This article tries to adopt data envelopment analysis window analysis to evaluate the technological innovation efficiencies of seven types of China's industrial enterprises during 2006–15. However, different window widths will lead to very different results. We designate the ideal window width through the scientific method rather than subjective judgments and obtain the efficiencies closer to reality. We also measure the efficiencies under the worst width opposite to the ideal window width to highlight differences. The results indicate that the efficiencies under the ideal width are more reasonable. During 2006–15, the efficiency of medium-sized enterprises was higher than that of large enterprises, that of private enterprises was higher than that of state-owned and state-holding enterprises, and that of foreign-funded enterprises was higher than that of enterprises with funds from Hong Kong, Macao, and Taiwan and that of domestic-funded enterprises. Moreover, the efficiencies of various types of enterprises all maintained upward trends.

**Key words:** DEA window analysis; technological innovation efficiency; industrial enterprises.

## 1. Introduction

China's economy has been growing very fast since the reforming and opening up in the late 1970s with rapid industrialization. According to the National Bureau of Statistics of China (2017), the value added of the industrial sector reached 24.8 trillion yuan (current price) in 2016, accounting for 33.3 percent of the country's GDP. However, the development of China's industrial sector has been driven mainly by resource inputs, accompanied by high investment, high consumption, and high greenhouse gas emissions. It consumed 2.92 billion tonnes of standard coal in 2015, accounting for 67.99 percent of the country's total energy consumption (National Bureau of Statistics of China 2017). This produces significant negative impacts on the environment and natural resources, including accounting for 56.67 percent of China's total industrial $CO_2$ emissions (Li and Lin 2016). Magat (1978) first affirmed that technological innovation cannot only reduce the pollution control cost but also advance production efficiency and profit margins through developing new products and improving the production process. It is an important factor in solving the environmental protection and enterprise economic performance. Currently, it is almost an axiom that technological innovation plays a crucial role in economic growth and environmental protection (Lin 2011). Hence, for China to transition to a more sustainable model of development and reduce its environmental impacts, it is very important to improve the innovation capability and efficiency of industrial enterprises.

In fact, as early as 2006, the Eleventh Five-Year Plan of China[1] had proposed to practically follow the new type of industrialization road and adhere to taking the market as the orientation, the enterprise as the principal part and the reinforcement of independent innovation ability as the central link to promote the integral technical level and comprehensive competitive force of industry and optimize and upgrade the industrial structure. Subsequently, the then-President Hu Jintao announced at the National Science and Technology Conference in 2006 that China was striving to build an innovation-oriented country by 2020 and making science and technology development a powerful support for economic and social development. In order to promote the construction of an innovation-oriented country, the 'National Medium- and Long-Term Plan for the Development of Science and Technology (2006–2020)'[2] was published in 2006. The plan proposed to increase investments in research and development to 2.5 percent of GDP and to reduce reliance on foreign technology by 30 percent by 2020. On 23 September 2012, the Chinese Government promulgated 'Opinions on Deepening the Reform of Science and Technology System and Accelerating the Construction of National Innovation System',[3] which was another programmatic document to guide the science and technology development of China. On 8 November 2012, the

Eighteenth National Congress of the Communist Party of China proposed implementing the strategy of innovation-driven development and indicated that 'scientific and technological innovation provides strategic support for raising the productive forces and boosting the overall national strength, and we must give it top priority in overall national development'.[4] The Chinese Government in 2016 promulgated the 'Outline of National Innovation-Driven Development Strategy'[5] and required all regions and departments to conscientiously carry it out on the basis of actual conditions. Moreover, the 'Made in China 2025' government-led initiative aimed at comprehensively upgrading the country's economic performance put forward two basic principles, namely, innovation-driven and green development, for its manufacturing sector (State Council of PRC 2016). These principles are leading China's current transformation. These all imply that China has paid more attention to scientific and technological innovation and placed it at a very important position since 2006. This is why we take 2006 as the starting point for the study.

The 'G20 2016 Innovation Action Plan'[6] noted, 'Innovation refers to the embodiment of an idea in a technology, product, or process that is new and creates value. ... Innovation covers a wide range of domains with science and technology innovation as the core.' Tidd and Bessant (2009) argued that innovation is a complex process and innovation inputs produce innovation outputs. The technological innovation efficiency is very important for increasing firm performance. It should not be evaluated as a single input or output activity. Cruz-Cázares et al. (2013) indicated that the best measurement of outcomes of technological innovations is through the efficiency with which they are developed. Evaluating innovation efficiency helps to identify the best innovation practitioners and sheds light on ways to improve efficiency by highlighting weaknesses. Hence, evaluations of innovation efficiency are receiving increased attention in research (Kou et al. 2016). At present, scholars mainly study the technological innovation efficiency at four levels: the national, regional, industrial, and enterprise levels.

First are studies at the national level. Wang (2007) applied the stochastic frontier methods to evaluate the technological innovation efficiency of thirty countries. Wang and Huang (2007) utilized the data envelopment analysis (DEA) approach to evaluate the technological innovation efficiency, accounting for environmental factors in thirty countries. Lee et al. (2010) evaluated the relative R&D efficiency of the hydrogen energy technology in thirty countries, applying the integrated fuzzy analytic hierarchy process and the DEA. Other similar studies include Grupp (1993), Sharma and Thomas (2008), Tseng (2009), Thomas et al. (2009), and Cullmann et al. (2012).

Second are studies at the regional level. Guan and Chen (2010) employed a relational network DEA model to measure the technological innovation efficiency of the high-tech industry in 26 regions of China from 2002 to 2003. Lin (2011) used panel data econometric analysis and Malmquist index analysis to calculate the technological innovation efficiency of thirty-one provinces in China from 1998 to 2007. Thomas et al. (2011) measured the technological innovation efficiency of fifty US states and the District of Columbia between 2004 and 2008. Zhong et al. (2011) applied the DEA model to calculate the technological innovation efficiencies of thirty regions in China in 2004. Wang et al. (2017) calculated the technological innovation efficiency of industrial sector in thirty provinces of China from 2001 to 2013 through the DEA–slacks based measure model.

Third are studies at the industrial level. Schmidtehmcke and Zloczysti (2011) measured the innovation efficiency of thirteen industries from seventeen countries from 2000 to 2004 based on the DEA model. Tang et al. (2009) analyzed the technological innovation efficiency of thirty-three industries involving large and medium-sized industrial enterprises over the period of 1999–2006 through the DEA approach. Bi et al. (2016) utilized factor analysis and a DEA-Tobit two-stage method to analyze the low-carbon technology innovation efficiency and its influencing factors in China's manufacturing industry in the period of 2008–12. Hong et al. (2016) applied the stochastic frontier model to analyze the innovation efficiency of seventeen high-tech industries in China from 2002 to 2011. Lee et al. (2017) estimated the technical innovation efficiency of the Korean information and communication technology industry from 2000 to 2013 through meta-frontier analysis. Xie and Wu (2017) measured the technological innovation efficiency of twenty industries in China between 2000 and 2012 using the super-efficiency DEA model.

Fourth are studies at the enterprise level. Díaz-Blateiro et al. (2006) analyzed the innovation efficiency of 171 Spanish wood-based firms for the years 1998–2001 using the DEA model. Guan et al. (2006) used the traditional DEA model to measure the innovation efficiency of 182 industrial innovative firms in China. Hashimoto and Haneda (2008) presented a DEA/Malmquist index method to measure the R&D efficiency change in Japanese pharmaceutical firms during 1983–92. Wei et al. (2013) employed the DEA model to measure the technical efficiency of China's non-ferrous metals firms in the period 2007–11. Cruz-Cázares et al. (2013) estimated the technological innovation efficiency of 415 Spanish manufacturing firms in nineteen industries for the period 1992–2005 using an intertemporal DEA bootstrap and a global Malmquist index. Wang et al. (2016) measured the technological innovation efficiency of thirty-eight Chinese new energy enterprises for 2009–13 utilizing a non-radial DEA approach. Feng et al. (2011) estimated the technological innovation efficiency of large- and medium-sized industrial enterprises across provinces in China during 2001–07 using the two-stage semi-parametric DEA approach. Luo and Sun (2010) applied the DEA model to estimate the technological innovation efficiency of large and medium-sized industrial enterprises in thirty provinces of China from 1996 to 2008. Pan and Yang (2014) used the adjusted DEA model based on the TOPSIS method excluding the influence of environmental factors to investigate the innovation efficiency of industrial enterprises across provinces in China in 2010.

Technological innovation efficiency in this article is defined as the input–output efficiency of technological innovation activities, namely, the relative capability of a firm to maximize innovation outputs given a certain quantity of innovation inputs (Cruz-Cázares et al., 2013). Sun and An (2016) noted that measuring the technological innovation efficiency from the perspective of input and output avoids separating the evaluation result and the technological innovation process. Therefore, this definition is widely used in the evaluation of technological innovation efficiency. The input–output efficiency is usually measured through parametric and non-parametric methods, as shown earlier. The parametric method first establishes a function with parameters and then estimates the unknown parameters using the method of least square or maximum-likelihood. However, the estimation results vary substantially due to the different functional forms chosen (Wang et al., 2017), and the form of production function sometimes limits the true relationship of parameters (Lin, 2011). Stochastic frontier analysis, for example, is a representative parametric method. The non-parametric method does not require a presumed function. Instead, it builds a minimal set of production possibilities covering all possible combinations between inputs and outputs. It can be seen as effective in obtaining the maximum output with given inputs or consuming the minimum inputs with given outputs. The most popular non-parametric method is DEA, which is widely used in evaluating the input–output efficiency of technological innovation (Luo and Liang, 2016). Zhou et al. (2008) summarized more than 100 articles in environmental and energy studies that have used this approach. As mentioned above, some previous DEA studies have examined the performance or efficiency of enterprises in the industrial sector.

Some applications are restricted to the use of standard DEA models, such as the Charnes, Cooper, and Rhodes (CCR) and Banker, Charnes, and Cooper (BCC) models based on cross-sectional data. They allow for the analysis of frontier shifts across different regions (Wang et al. 2016), stages (Chun et al. 2017), actors (Bae and Chang 2012), core technologies (Kim 2017), or returns to scale (Liu et al. 2017) but not time. However, it is very important for policymakers that the models be able to detect efficiency trends over time. As Kumbhakar and Lovell (2000: 10) note, 'Cross-sectional data provide a snapshot of producers and their efficiency. Panel data provide more reliable evidence on their performance, because they enable us to track the performance of each producer through a sequence of time periods.' Hence, Charnes and Cooper (1985) developed the DEA window analysis to compensate for this defect. The DEA window analysis can handle panel data comprising both time-series and cross-sectional samples. The results obtained in this way provide trends in efficiency over time, evaluating and ranking each decision-making unit (DMU) according to its effectiveness. Moreover, DEA window analysis can observe how each DMU performs in different periods so that the number of DMUs increases and the discriminating power also increases (Yang and Chang 2009).

Studies that have applied DEA window analysis to evaluate efficiencies over time include Sueyoshi and Aoki (2001), who combine DEA window analysis with the Malmquist index to evaluate the performance of Japanese postal services during 1983–97; Asmild et al. (2004), who also combine DEA window analysis with the Malmquist index to calculate productivity change from 1981 to 2000 for Canada's banking industry; and Sueyoshi et al. (2013), who measure the efficiency of US coal-fired power plants during 1995–2007. Specifically for China, Wang et al. (2013) utilized DEA window analysis to examine the energy and environmental efficiency of twenty-nine administrative regions during 2000–08. The list of studies further includes Charnes and Cooper (1985), Hartman and Storbeck (1996), Ross and Droge (2002), Webb (2003), Cullinane et al. (2004), and Cooper et al. (2007).

Despite this, until now, DEA window analysis has appeared relatively rarely in the literature, particularly for measuring the efficiencies of enterprises or industries. Moreover, most previous studies using DEA window analysis select the window width through subjective judgments; for example, Cullinane et al. (2004), Halkos and Tzeremes (2009), Řepková (2014), and Vlontzos and Pardalos (2017) all chose a 3-year window. Such judgments are arbitrary, and a change in the window width would obviously have an impact on the efficiency value (Chen et al., 2013). Therefore, Chen et al. (2013) proposed a method for determining the ideal window width. Its basic rationale is to first analyze the discrepancy between the efficiency value under each window width and the average of all efficiency values under different window widths and then designate the window width with the smallest discrepancy as the ideal window width. Section 2 provides a detailed illustration of this.

Although technological innovation efficiency has been of interest for many studies, the attention given to enterprises is relatively limited and has the following drawbacks. First, most studies focus on the efficiency of countries, regions, or industries. There are not many studies on technological innovation efficiency across enterprises in the industrial sector. However, innovation is particularly important for the development of industrial enterprises, and improving technological innovation efficiency can help enterprises to achieve greater performance as well as to establish and strengthen their core competitiveness (Albort-Morant et al. 2016). Therefore, it is very significant to evaluate innovation efficiency of enterprises and then improve efficiency by identifying and overcoming weaknesses. As is well known, in China, different types of enterprises generally differ in corporate system, innovation environment and innovation policy, which would greatly influence the technological innovation efficiency. Which type of corporate system and policy are more suitable for technological innovation? We can determine the answer through evaluating the technological innovation efficiencies of different types of enterprises. However, few studies do so. Second, most studies employ traditional DEA models based on cross-sectional data but not panel data to examine the efficiency and cannot provide dynamic efficiency trends over time. Third, the studies that use DEA window analysis tend to select the window width subjectively and arbitrarily, which is likely to reduce the credibility and robustness of the research.

As such, this study utilizes DEA window analysis with ideal window width to examine the technological innovation efficiencies of seven types of enterprises in the industrial sector of China during the period 2006–15. To the best of our knowledge, this is the first application of DEA window analysis with an ideal window width for Chinese enterprises. The results reveal the dynamic trends of the technological innovation efficiency of each type of enterprise as well as inter-enterprise disparities. Furthermore, the study compares the results with those calculated with DEA window analysis with the worst window width.

The remainder of the article is organized as follows. Section 2 outlines DEA window analysis with an ideal window width. The variables and data used in the study are presented in Section 3. Section 4 shows the empirical results including a comparative analysis. The final section concludes the article.

## 2. DEA window analysis with an ideal window width

DEA, first proposed by Charnes et al. (1978), is a non-parametric linear programming approach to measure efficiency, capable of handling multiple inputs and multiple outputs (Asmild et al. 2004). The traditional DEA model, for example, the CCR model introduced by Charnes et al. (1978), is performed over only one time period and cannot measure efficiency changes over time. Therefore, Charnes and Cooper (1985) proposed DEA window analysis, a variation of the traditional DEA approach, to measure efficiency in cross-sectional and time-varying data and allow for dynamic effects. The window analysis technique works on the principle of moving averages (Charnes et al. 1995; Asmild et al. 2004; Cooper et al. 2007). Its rationale is that each DMU in a window is treated as entirely different, which enables comparison of a DMU's efficiency in a particular period with its behavior in other periods (Yang and Chang, 2009). Thus, it increases the number of DMUs in the sample so that the small sample sizes problem and the robustness-related problems can be resolved (Yang and Chang 2009; Řepková 2014). Moreover, the efficiency of a DMU in a period can be contrasted against itself and against other DMUs over time (Asmild et al. 2004). As indicated by Hartman and Storbeck (1996) and Webb (2003), DEA window analysis can provide efficiency trends over a specified period of time and simultaneously examine the stability and other properties of the efficiency evaluations across as well as within the specified windows.

In view of this, we apply DEA–CCR window analysis to measure the technological innovation efficiencies of seven types of enterprises in the industrial sector of China over the period 2006–15. The approach is briefly described below. In practice, various types of enterprises or DMUs might face either economies or diseconomies of scale in technological innovation. It may be more appropriate to assess the technological innovation efficiency using the BCC model with variable returns to scale. However, the BCC model can measure only the pure technical efficiency (PTE). We argue that the technological innovation efficiency of various types of enterprises should include not only PTE but also scale efficiency (SE). The overall technical efficiency calculated by the CCR model, comprising both PTE and SE, is more practically meaningful than PTE calculated by the BCC model. Moreover, those DMUs indicated as efficient in the BCC model are efficient only in relation to others in the sample. It may be possible for a unit outside the sample to achieve higher efficiency than the best-practice DMU in the sample (Řepková 2014). In other words, there may still be room for those DMUs to improve the efficiency. On the other hand, the efficiency scores calculated based on the input-oriented BCC model are not equal to those calculated based on the output-oriented BCC model, but the CCR model does not have this problem. For the technological innovation efficiencies of various types of enterprises, the innovation inputs and innovation outputs are equally important and need be considered simultaneously. Therefore, the CCR model is more appropriate to assess the efficiency.

Adopting the formalization by Asmild et al. (2004) and Gu and Yue (2011), consider $N$ DMUs ($n = 1, \ldots, N$) observed in $T$ ($t = 1, \ldots, T$) periods using $r$ inputs and $s$ outputs. The sample is $N \times T$ observations, where an observation $n$ is in period $t$. $\mathrm{DMU}_t^n$ represents $\mathrm{DMU}^n$ in period $t$ with an $r$-dimensional input vector $X_t^n = (x_{1t}^n, x_{2t}^n, \ldots x_{rt}^n)'$ and $s$-dimensional output vector $Y_t^n = (y_{1t}^n, y_{2t}^n, \ldots y_{st}^n)'$. If a window starts at time $k$, $1 \le k \le T$, with width $j$, $1 \le j \le T\text{-}k$, the matrices of inputs and outputs are given as follows:

$$X_{kj} = (x_k^1, x_k^2, \ldots x_k^N, x_{k+1}^1, x_{k+1}^2, \ldots x_{k+1}^N, \ldots x_{k+j}^1, x_{k+j}^2, \ldots x_{k+j}^N) \quad (1)$$

$$Y_{kj} = (y_k^1, y_k^2, \ldots y_k^N, y_{k+1}^1, y_{k+1}^2, \ldots y_{k+1}^N, \ldots y_{k+j}^1, y_{k+j}^2, \ldots y_{k+j}^N) \quad (2)$$

The CCR model of the DEA window problem for $\mathrm{DMU}_t^k$ is given by solving the linear program as follows:

$$\begin{aligned} &\min\theta \\ &s.t. \\ &\theta \cdot x_t' - X_{kj}\lambda \ge 0 \\ &Y_{kj}\lambda - y_t' \ge 0 \\ &\lambda_n \ge 0 \ (n = 1, 2 \ldots, N \times j) \\ &1 \le t \le T, 1 \le n \le N \end{aligned} \quad (3)$$

As indicated above, most previous studies select the window width through subjective judgments. They generally designate 3 as the window width, for example, Cullinane et al. (2004), Halkos and Tzeremes (2009), Wang et al. (2013), Řepková (2014), and Vlontzos and Pardalos (2017). However, Chen et al. (2013) argued that the change in window width would obviously produce effects on the efficiency value and different widths will lead to very different results. The method proposed by Chen et al. (2013) to determine the ideal window width is explained as follows.

According to Eq. (3), we calculate the efficiency of each type of industrial enterprises in period $i$ with window width $j$ (from 1 to $T$) and obtain the average efficiency value for the seven types of industrial enterprises in period $i$ with window width $j$, which is denoted as $M_{ij}$. $\mathrm{Mean}^i$ represents the mean of $M_{ij}$ in period $i$. Then, the deviation ratio of $M_{ij}$ and $\mathrm{Mean}^i$ is represented by $v_{ij}$, as shown in Eq. (4). $v_{ij}$ represents the discrepancy between the efficiency value under window width $j$ and the average of all efficiency values under different window widths in period $i$. The smaller $v_{ij}$ is, the smaller the difference between the efficiency value under window width $j$ and the average of all efficiency values under different window widths, indicating the closer the efficiency value under window width $j$ is to stable efficiency value and reality for China's enterprises. The matrix $V$ is shown in Eq. (5). The minimum absolute value in row $i$ in matrix $V$ is denoted as $v_{ij0}$, shown in Eq. (6). We designate the window width with the largest number of $v_{ij0}$ as the ideal window width. According to Eqs. (7) and (8), we obtain matrix $U$. Finally, we calculate the sum of $u_{ij}$ in column $j$, which is named $c_j$ shown in Eq. (9), and then obtain matrix $C$, as shown in Eq. (10). The maximum absolute value of $c_j$ ($1 \le j \le T$) is denoted as $c_{j0}$, as shown in Eq. (11). When $c_j$ in matrix $C$ equals $c_{j0}$, $j$ is the ideal window width.

Three cases may occur. (1) If there is only one $c_j$ equal to $c_{j0}$, then the ideal window width is $j$. (2) If there are multiple $c_j$ equal to $c_{j0}$, the minimum $j$ is the ideal window width. (3) If the values of all $c_j$ are equal to $c_{j0}$, the ideal window cannot be determined, and it can only be decided based on experience.

$$v_{ij} = \frac{M_{ij} - \mathrm{Mean}^i}{\mathrm{Mean}^i} \times 100\% \quad (4)$$

$$V = \begin{bmatrix} v_{11}, v_{12}, \ldots & v_{1T} \\ v_{21}, v_{22}, \ldots & v_{2T} \\ \ldots\ldots\ldots\ldots & \ldots \\ v_{T1}, v_{T2}, \ldots & v_{TT} \end{bmatrix}_{T \times T} \quad (5)$$

$$v_{ij0} = \min_{1 \le j \le T}(|v_{ij}|) \quad (6)$$

$$u_{ij} = \begin{cases} 1, & \text{when} \quad |v_{ij}| = v_{ij0} \\ 0, & \text{when} \quad |v_{ij}| \ne v_{ij0} \end{cases} \quad (7)$$

$$U = \begin{bmatrix} u_{11}, u_{12}, \ldots & u_{1T} \\ u_{21}, u_{22}, \ldots & u_{2T} \\ \ldots\ldots\ldots\ldots & \ldots \\ u_{T1}, u_{T2}, \ldots & u_{TT} \end{bmatrix}_{T \times T} \quad (8)$$

$$c_j = \sum_{i=1}^{T} u_{ij}, (1 \le j \le T) \quad (9)$$

$$C = (c_1, c_2, \ldots, c_T)_{1 \times T} \quad (10)$$

$$c_{j0} = \max_{1 \le j \le T}(c_j) \quad (11)$$

## 3. Variables and data

### 3.1 Input and output variables

In this study, we use three inputs and three outputs to measure the efficiency of technological innovation. The inputs include personnel, namely, R&D personnel, capital, namely, investment in technical renovation and internal R&D investment. As personnel engaged in R&D activities is the most direct input in technological innovation, we consider the full-time equivalent of R&D personnel as the first input variable (Guan and Chen 2010; Hong et al. 2016). Capital inputs in technological innovation include investment in technical renovation and R&D activities. Investment in technical renovation, measured by expenditure for technical renovation, is the second input (Yin and Chen 2016). Generally, R&D investment can be internal or external. As internal R&D investment can reflect better the innovation intensity of an industry (Cruz-Cázares et al. 2013; Hong et al. 2016), this is the third input.

Due to the accumulative and time-lag effects, the estimation of capital investment is calculated as follows (Yu and Liu, 2013):

$$K_{it} = I_{it} + (1-\delta)\cdot K_{i(t-1)} \tag{12}$$

where $K_{it}$ represents the stock of investment in technical renovation or R&D activities in industry $i$ at year $t$; $I_{it}$ represents the annual added investment in technical renovation or R&D activities in industry $i$ at year $t$; δ represents the depreciation rate for investment, which is generally set up as 15 percent.

$$K_{i0} = I_{i0}/(g_i + \delta) \tag{13}$$

where $g_i$ denotes the average annual growth rate of investment in industry $i$ during 2006–15.

The outputs are the number of invention patent applications (Revilla et al. 2003; Cruz-Cázares et al. 2013), number of new product development (NPD) projects (Choi et al. 2016) and sales revenue from new products (Guan and Chen 2010), deflated by the Producer Price Index for industrial products. As Choi et al. (2016) indicated, the expansion of investments in NPD along with the accumulation of product innovation leads to an increase in the number of NPD projects, thereby accelerating the introduction of new products and increasing the profit of the enterprise. Hence, the number of NPD projects is the second output.

According to Brown and Svenson (1998), Furman et al. (2002), Wang and Huang (2007), and Guan and Chen (2010), a corresponding relationship between input and output variables is very important for obtaining meaningful efficiency measures. However, it is often difficult and even sometimes impossible to directly choose observable measurable outputs to correctly match the corresponding inputs, particularly for commercial profit measures in the knowledge commercialization process (Guan and Chen, 2012). Isolating the contribution of innovation to enterprise performance from that of other business activities can be challenging (Kerssens-van Drongelen et al. 2000).

Here, the input and output variables in the DEA model are thought of as disposable for activity-practitioners and are usually physical indicators and measured using statistical and observable aggregate values. In essence, they are the part factors in the production process and should be considered in defining the production possibilities set. Therefore, Moon and Lee (2005), Wang and Huang (2007), and Guan and Chen (2010) advise to select the representative input and corresponding output variables to define the production possibilities set in performance assessments and ensure fair comparisons.

The inputs for the technological innovation activities influence the level of technological innovation in the enterprise (measured by the number of invention patent applications). Then, the change in the technological innovation level influences the economic benefits (measured by the number of NPD projects and the sales revenue from new products) from the enterprise.

### 3.2 Data sources

In China, industrial enterprises are divided into seven types based on three standards. First, industrial enterprises are divided into large- and medium-sized enterprises based on the size of enterprises. Second, industrial enterprises are divided into state-owned and state-holding enterprises and private-owned enterprises based on the ownership of enterprises. Third, industrial enterprises are divided into domestic-funded enterprises, enterprises with funds from Hong Kong, Macao, and Taiwan, and foreign-funded enterprises based on the sources of funds of enterprises. We will dynamically evaluate the technological innovation efficiencies of these seven types of enterprises in the next section. The data for all variables are obtained from Statistics Yearbook on Science and Technology Activities of Industrial Enterprises from 2007 to 2016.

## 4. Empirical results and analysis

### 4.1 Evaluation using DEA window analysis with ideal window width

As previously explained, this study employs the DEA–CCR window analysis with ideal window width to measure the technological innovation efficiency for seven types of enterprises in the industrial sector of China during 2006–15. The model estimation is carried out using the software DEA-SOLVER Pro5. Table 1 shows the values of $v_{ij}$ under window width 1–10 and $v_{ij0}$.

According to the methodology introduced in Section 2, $c_6$ equals 4, $c_7$ and $c_8$ both equal 3, $c_3$, $c_4$, and $c_5$ both equal 2, and $c_2$, $c_9$, and $c_{10}$ both equal 1; thus, $c_6$ is the maximum among $c_j$. Thus, the ideal window width is 6. We then calculate the technological innovation efficiency for seven types of enterprises in the industrial sector using the model with ideal window width of 6. The results are presented in Table 2 and Fig. 1. Figure 1 shows the dynamic change of efficiency for each type of enterprise and the inter-enterprise differences through three-dimensional graphics.

During the period 2006–14, the technological innovation efficiency of medium-sized enterprises was consistently higher than that of large enterprises, and the former's average efficiency was 0.108 higher than the latter's. The result is consistent with our expectancies. Cruz-Cázares et al. (2013) also indicated that small- and medium-sized enterprises can make the most of their limited resources. For a long time, China's medium-sized enterprises have consistently had a stronger motivation for technological innovation and are the mainstay of technological innovation. While the motivation for innovation in large enterprises generally is lower, due to the strict rules and regulations greatly constraining the innovators (Wu 2009). Moreover, medium-sized enterprises have much lower trial and error costs than large enterprises; thus, they often act in a pathfinder role for the new technologies and new products and pave the way for large enterprises to integrate technologies. Therefore, large enterprises have lower initiative and enthusiasm for technological innovation than medium-sized enterprises, which leads to lower technological innovation efficiency. However, along with increasing attention to science and technology innovation as well as accelerating the construction of innovation-oriented country and innovation-driven strategy of China, the technological innovation efficiency of large enterprises has also been increasing.

In 2006, the technological innovation efficiency of state-owned and state-holding enterprises was the lowest among all types of enterprises, at only 0.272. However, it increased fastest, reaching 1 in 2015. The result implies that the technological innovation of state-owned and state-holding enterprises has been developing very rapidly, and the efficiency has been continuously improved in the period of 2006–15, along with the continuous promotion of the

**Table 1.** Values of $v_{ij}$ under window width 1–10 and $v_{ij0}$ during the period 2006–15.

| Window width | $v_{i1}$ (%) | $v_{i2}$ (%) | $v_{i3}$ (%) | $v_{i4}$ (%) | $v_{i5}$ (%) | $v_{i6}$ (%) | $v_{i7}$ (%) | $v_{i8}$ (%) | $v_{i9}$ (%) | $v_{i10}$ (%) | $v_{ij0}$ (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | | | | | | | | | | | |
| 2006 | 59.89 | **−6.65** | **−6.65** | **−6.65** | **−6.65** | **−6.65** | **−6.65** | **−6.65** | **−6.65** | **−6.65** | 6.65 |
| 2007 | 2.71 | 0.99 | 0.99 | 0.99 | 0.49 | **−0.12** | −0.94 | −1.48 | −1.76 | −1.88 | 0.12 |
| 2008 | 55.73 | 12.71 | **−0.93** | −2.04 | −2.16 | −2.36 | −2.61 | −2.84 | −27.64 | −27.85 | 0.93 |
| 2009 | 36.43 | 35.65 | 11.80 | **−0.80** | −1.65 | −2.15 | −2.64 | −12.61 | −31.97 | −32.07 | 0.80 |
| 2010 | 32.91 | 24.38 | 21.85 | 7.20 | **−0.70** | −1.08 | −6.56 | −14.86 | −31.40 | −31.74 | 0.70 |
| 2011 | 14.96 | 13.80 | 13.08 | 12.74 | 6.10 | **−0.82** | −4.81 | −10.50 | −22.11 | −22.44 | 0.82 |
| 2012 | 12.82 | 9.96 | 9.42 | 9.05 | 8.77 | **2.19** | −4.90 | −9.35 | −18.75 | −19.20 | 2.19 |
| 2013 | 9.62 | 8.07 | 7.35 | 7.12 | 7.05 | 7.05 | **−0.61** | −9.05 | −17.95 | −18.64 | 0.61 |
| 2014 | 5.91 | 5.33 | 4.95 | 4.82 | 4.82 | 4.80 | 4.78 | **−4.77** | −14.87 | −15.77 | 4.77 |
| 2015 | 5.76 | 3.46 | 3.45 | 3.43 | 3.43 | 3.43 | **3.36** | **3.36** | −14.84 | −14.84 | 3.36 |

The bold value signify the minimum absolute value in row *i* in matrix V.

**Table 2.** Average value of technological innovation efficiency for each type of enterprise under the ideal window width of 6 during the period 2006–15.

| Year | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | Average value | Standard deviation |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Enterprise | | | | | | | | | | | | |
| Large enterprises | 0.336 | 0.359 | 0.470 | 0.584 | 0.583 | 0.641 | 0.719 | 0.822 | 0.881 | 0.964 | 0.602 | 0.213 |
| Medium-sized enterprises | 0.462 | 0.419 | 0.584 | 0.710 | 0.728 | 0.750 | 0.883 | 0.980 | 0.974 | 0.876 | 0.710 | 0.199 |
| State-owned and state-holding enterprises | 0.272 | 0.289 | 0.436 | 0.578 | 0.585 | 0.642 | 0.705 | 0.775 | 0.877 | 1.000 | 0.569 | 0.238 |
| Private enterprises | 1.000 | 0.884 | 0.766 | 0.823 | 0.801 | 0.988 | 1.000 | 1.000 | 1.000 | 1.000 | 0.921 | 0.097 |
| Domestic-funded enterprises | 0.326 | 0.354 | 0.484 | 0.625 | 0.614 | 0.745 | 0.857 | 0.940 | 0.992 | 1.000 | 0.647 | 0.254 |
| Enterprises with funds from Hong Kong, Macao, and Taiwan | 0.515 | 1.000 | 0.630 | 0.695 | 0.689 | 0.836 | 0.909 | 0.970 | 0.978 | 1.000 | 0.803 | 0.177 |
| Foreign-funded enterprises | 0.717 | 0.757 | 0.727 | 0.787 | 0.898 | 0.952 | 0.963 | 1.000 | 1.000 | 1.000 | 0.873 | 0.120 |

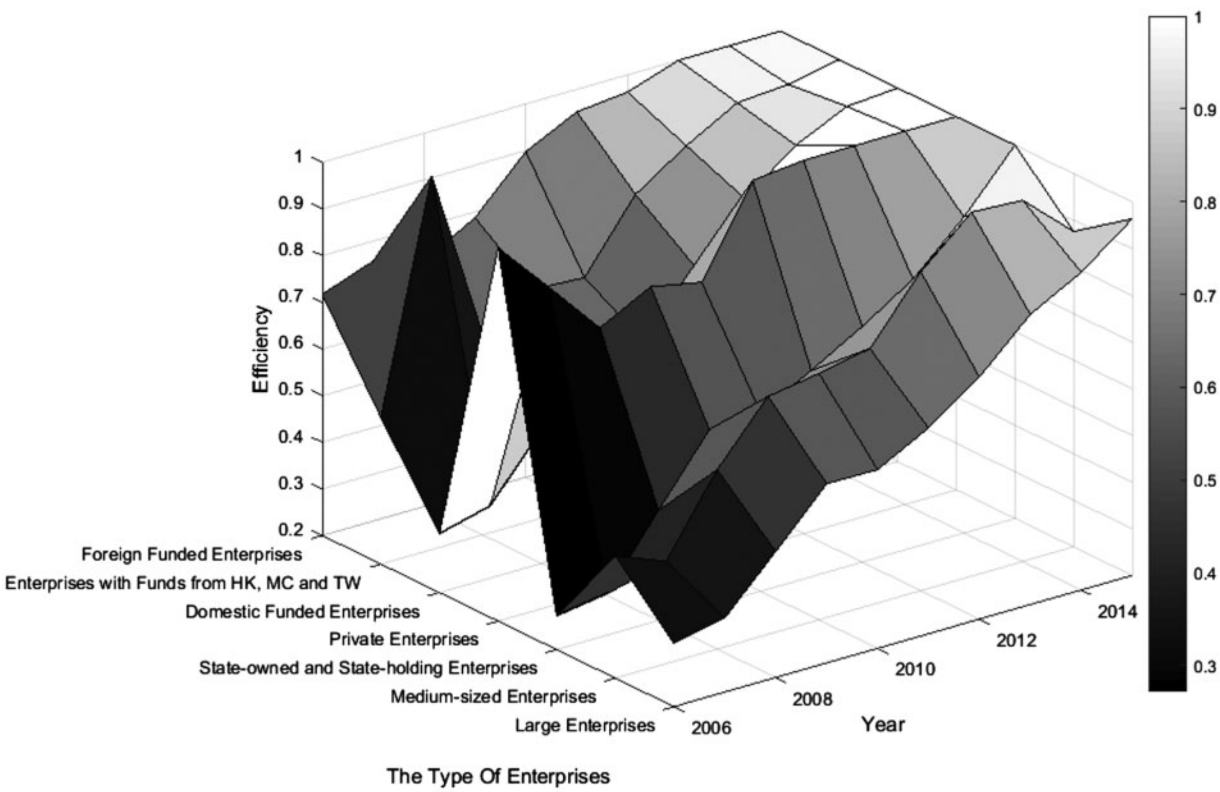


**Figure 1.** Average value of technological innovation efficiency for each type of enterprises under the ideal window width of 6 during the period 2006–15.

reform of state-owned enterprises in China. Private enterprises have always been more efficient in technology innovation than state-owned and state-holding enterprises, except in 2015. The efficiency value of private enterprises had reached 1 for 5 years between 2006 and 2015. The result is consistent with our expectations. China's private enterprises have always had strong innovation capacity. For example, Alibaba, Tencent, and Huawei, which are all private enterprises, are the only three Chinese companies in the list of the most innovative companies in 2017 (The Boston Consulting Group 2018). Their innovative capacities and efficiencies are much higher than state-owned and state-holding enterprises. Overall, the technological innovation efficiency of private enterprises changed little, with a standard deviation of 0.097. However, the efficiency value rapidly decreased from 1 to 0.766 during the period 2006–8, which might be because of the influence of the international financial crisis. Most Chinese private enterprises depended greatly on foreign trade; thus, their performances were hit by the rapid drop in international market demand during the crisis, which led to a rapid decline in technological innovation efficiency. Along with the slowly recovering international economy and Chinese economy, the efficiency of private enterprises rose from 0.823 in 2009 to 1 in 2012 and remained constant thereafter.

Compared with enterprises with funds from Hong Kong, Macao, and Taiwan, and foreign-funded enterprises, domestic-funded enterprises have consistently had the lowest technological innovation efficiency during the period 2006–14. However, their efficiency rose fastest, increasing by 0.674 in the period of 2006–15. The technological innovation efficiency of foreign-funded enterprises was often higher than that of enterprises with funds from Hong Kong and Macao except for in 2007 and 2015. The efficiency of enterprises with funds from Hong Kong and Macao was at the middle level among these three types of enterprises. The result is consistent with our expectations. Generally, compared with domestic-funded enterprises, foreign-funded enterprises, and enterprises with funds from Hong Kong, Macao, and Taiwan have relatively more advanced management concepts and pay more attention to technological innovation, with more investment in innovation, a more perfect innovation system and a better innovation environment. Hence, their innovation outputs and efficiencies are also relatively higher. However, with the deepening of China's reform and opening up, domestic-funded enterprises have developed rapidly and have been paying more attention to technological innovation. Their innovation efficiency and capacity are also increasing fast.

### 4.2 Comparative analysis

Chen et al. (2013) indicated that the change in window width would obviously produce effects on the efficiency value, and different widths will lead to very different results. Therefore, in addition to DEA window analysis with the ideal window width, Chen et al. (2013) also proposed DEA window analysis with the worst window width. They defined the window width with the largest number of maximum deviations [$v'_{ij0} = \max(|v_{ij}|)$] as the worst window width. In order to highlight the need to assess the efficiency with the ideal window width, we will compare the results under the worst window width with those under the ideal window width.

Table 1 shows that there are five maximum deviations under window widths of both 1 and 10. Therefore, window widths of both 1 and 10 are the worst window widths. We recalculate the efficiency of each type of enterprises using DEA window analysis with the window widths of 1 and 10 and compare it with the above results. The model estimations are also carried out using the software DEA-SOLVER Pro5 with the efficiency values presented in Tables 3–4 and Figs 2–3.

In order to better compare the efficiencies calculated under different window widths, Fig. 4 shows the average values of technological innovation efficiencies of various types of enterprises under different window widths and the deviations between them. Deviation 1–6 represents the deviation between the average efficiencies under window widths of 1 and 6, and deviation 10–6 represents the deviation between the average efficiencies under window widths of 10 and 6, namely, deviation 1–6 = $(M_1–M_6)/M_6$ and deviation 10–6 = $(M_{10}–M_6)/M_6$; therein, $M_1$, $M_6$, and $M_{10}$ are the average efficiencies, respectively, under window widths of 1, 6, and 10.

In summary, compared with the DEA window analysis with ideal window width, the DEA window analysis with the worst window width generates significantly different results. The efficiency values for various types of enterprises under the ideal window width of 6 are generally lower than those under the window width of 1 but higher than those under the window width of 10, and the number of DEA efficient enterprises under the ideal window width of 6 is less than that under the window width of 1 but more than that under the window width of 10. This finding means that the efficiency values under the window width of 1 are overvalued, while those under the window width of 10 are undervalued. Moreover, the absolute values of deviation 1–6 and deviation 10–6 are all larger than 5 percent, mostly larger than 20 percent. This implies that the choice of window width produces an important effect on the result. It is necessary to select the ideal window width to obtain more accurate and realistic results (Chen et al. 2013).

During the period 2006–15, regardless of the window width, one common result is that technological innovation efficiency of medium-sized enterprises was higher than that of large enterprises, that of private enterprises was higher than that of state-owned and state-holding enterprises, and that of foreign-funded enterprises was higher than that of enterprises with funds from Hong Kong, Macao, and Taiwan and that of domestic-funded enterprises.

## 5. Conclusions

There have been many studies on technological innovation efficiency at the national, regional, industrial levels, and on the impact of technological innovation on economic growth or total factor productivity. They, however, have paid little attention to the efficiencies of various types of enterprises in the industrial sector of China, and most studies cannot provide dynamic efficiency trends over time as a result of using traditional DEA models based on cross-sectional data.

This is one of the few studies to apply DEA window analysis with ideal window width to measure the technological innovation efficiency for various types of enterprises in the industrial sector of China during the period 2006–15. This approach favors the commonly used panel data analysis. Furthermore, we compared the results with those under the worst window width.

The obtained empirical results show the following.

(1) The ideal window width in this study is 6, and the worst window widths are 1 and 10. The efficiencies calculated by DEA window analysis with ideal window width are more reasonable than those calculated by DEA window analysis with the worst window width of 1 and 10. The efficiency values for various types of enterprises under the ideal window width are generally lower than those

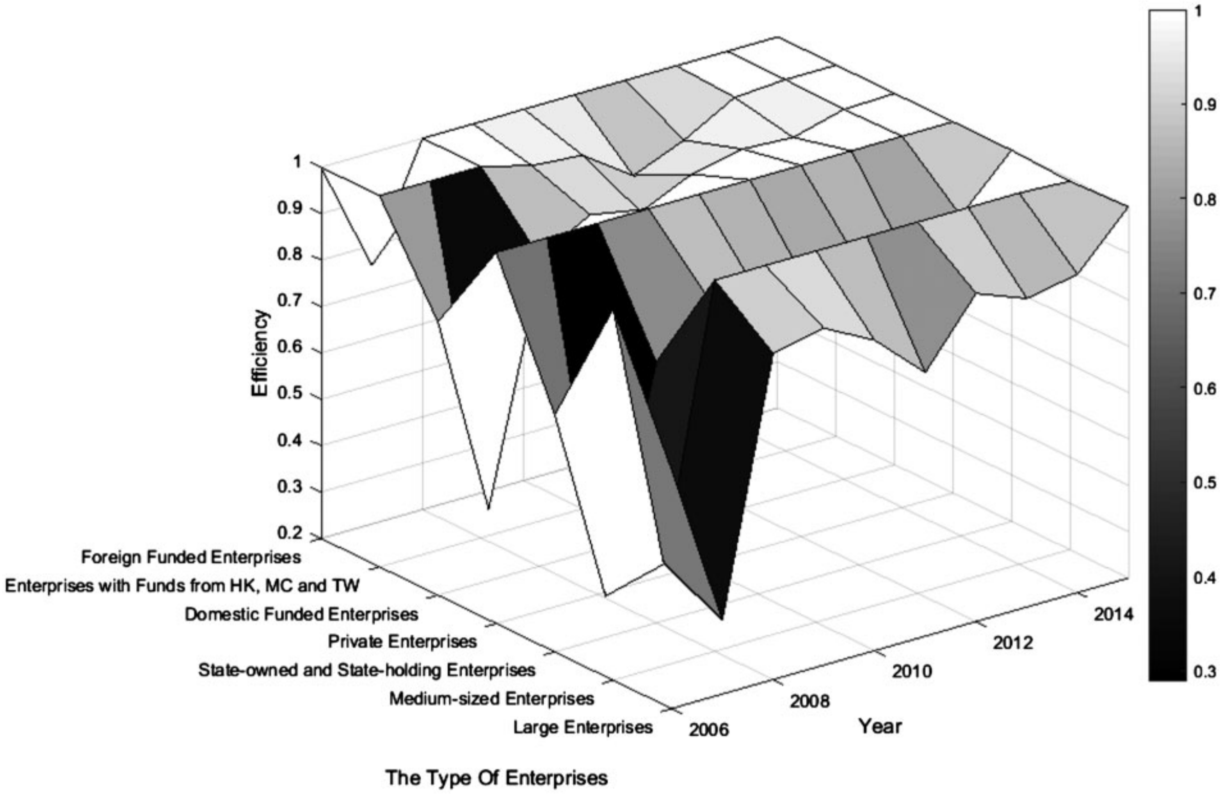


**Figure 2.** Average value of technological innovation efficiency for each type of enterprises under the window width of 1 during the period 2006–15.

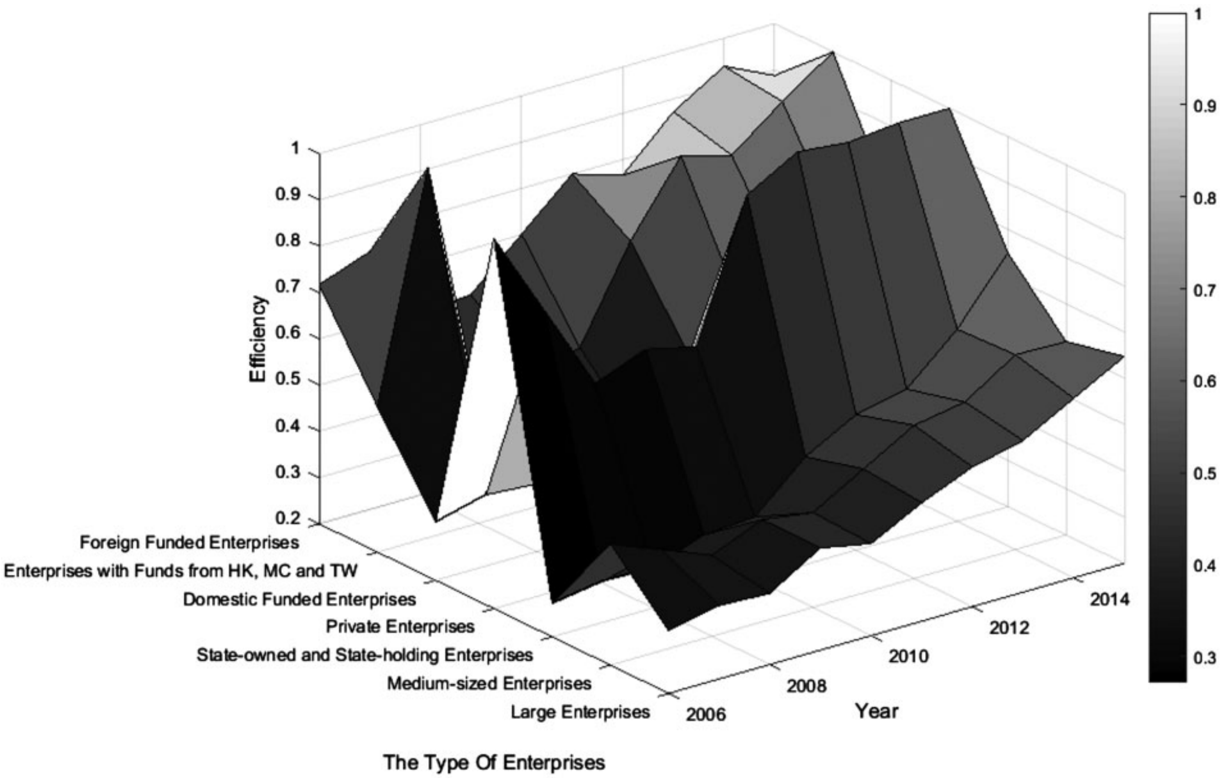


**Figure 3.** Average value of technological innovation efficiency for each type of enterprises under the window width of 10 during the period 2006–15.

**Table 3.** Average value of technological innovation efficiency for each type of enterprises under the window width of 1 during the period 2006–15.

| Year | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | Average value | Standard deviation |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Enterprise | | | | | | | | | | | | |
| Large enterprises | 0.715 | 0.359 | 0.903 | 0.926 | 0.869 | 0.768 | 0.907 | 0.865 | 0.886 | 1.000 | 0.794 | 0.180 |
| Medium-sized enterprises | 1.000 | 0.419 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.994 | 0.916 | 0.18 |
| State-owned and state-holding enterprises | 0.711 | 0.289 | 0.762 | 0.873 | 0.849 | 0.830 | 0.850 | 0.816 | 0.890 | 1.000 | 0.754 | 0.191 |
| Private enterprises | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.000 |
| Domestic-funded enterprises | 0.789 | 0.354 | 0.867 | 0.926 | 0.901 | 0.951 | 0.974 | 0.968 | 0.997 | 1.000 | 0.843 | 0.193 |
| Enterprises with funds from Hong Kong, Macao, and Taiwan | 1.000 | 1.000 | 1.000 | 0.971 | 0.962 | 0.887 | 0.932 | 0.993 | 1.000 | 1.000 | 0.974 | 0.038 |
| Foreign-funded enterprises | 1.000 | 0.757 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.973 | 0.077 |

**Table 4.** Average value of technological innovation efficiency for each type of enterprises under the window width of 10 during the period 2006–15.

| Year | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | Average value | Standard deviation |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Enterprise | | | | | | | | | | | | |
| Large enterprises | 0.336 | 0.359 | 0.354 | 0.421 | 0.399 | 0.456 | 0.502 | 0.528 | 0.588 | 0.647 | 0.449 | 0.105 |
| Medium-sized enterprises | 0.462 | 0.419 | 0.375 | 0.421 | 0.405 | 0.468 | 0.531 | 0.550 | 0.621 | 0.618 | 0.480 | 0.088 |
| State-owned and state-holding enterprises | 0.272 | 0.289 | 0.287 | 0.327 | 0.334 | 0.433 | 0.493 | 0.517 | 0.615 | 0.749 | 0.407 | 0.161 |
| Private enterprises | 1.000 | 0.813 | 0.625 | 0.667 | 0.641 | 0.938 | 1.000 | 0.989 | 1.000 | 1.000 | 0.852 | 0.164 |
| Domestic-funded enterprises | 0.326 | 0.354 | 0.346 | 0.403 | 0.383 | 0.531 | 0.611 | 0.635 | 0.701 | 0.730 | 0.480 | 0.157 |
| Enterprises with funds from Hong Kong, Macao, and Taiwan | 0.515 | 1.000 | 0.447 | 0.493 | 0.517 | 0.716 | 0.869 | 0.839 | 0.924 | 1.000 | 0.700 | 0.222 |
| Foreign-funded enterprises | 0.717 | 0.757 | 0.591 | 0.602 | 0.701 | 0.800 | 0.766 | 0.872 | 0.939 | 0.888 | 0.755 | 0.116 |

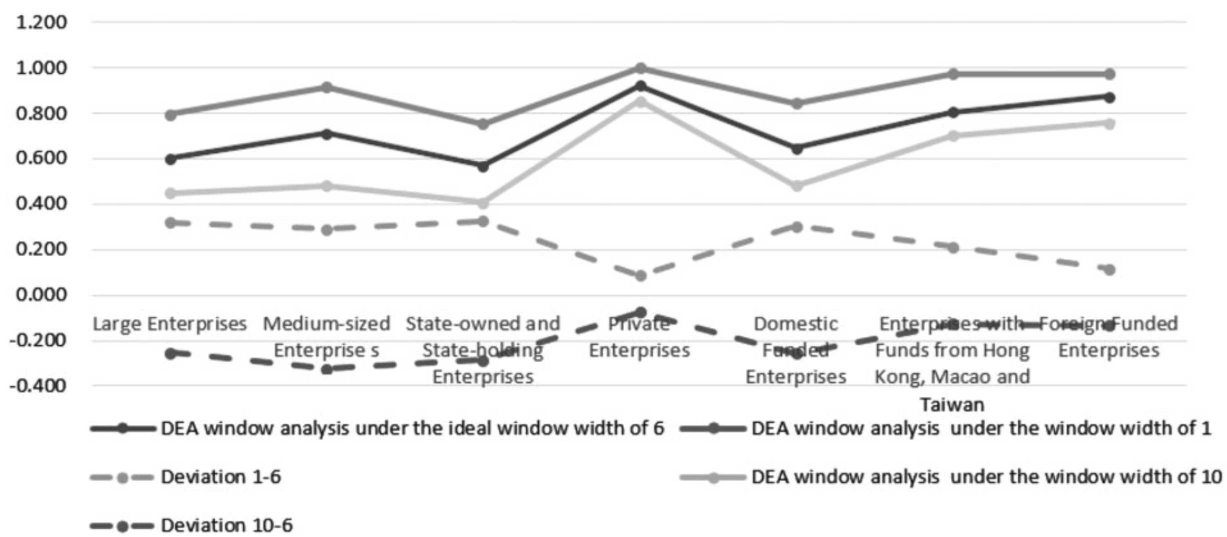


**Figure 4.** Deviations of efficiencies calculated respectively by DEA window analysis with different window widths.

under the window width of 1, but higher than those under the window width of 10. This finding implies that compared with the ideal window width, the efficiency values under the window width of 1 are overvalued, while those under the window width of 10 are undervalued. The calculated efficiencies under the ideal window width in this study are more realistic than those obtained under the worst window width. Therefore, this should be a preferred method for analysis.

(2) During the period 2006–15, the technological innovation efficiency of medium-sized enterprises was higher than that of large enterprises, that of private enterprises was higher than that of state-owned and state-holding enterprises and that of foreign-funded enterprises was higher than that of enterprises with funds from Hong Kong, Macao, and Taiwan and that of domestic-funded enterprises.

(3) The technological innovation efficiencies of various types of enterprises all maintained upward-trends during the period 2006–15. State-owned and state-holding enterprises, domestic-funded enterprises and large enterprises increased relatively faster.

In the future, more attention should be paid to improving the efficiency of various types of enterprises, particularly large enterprises, state-owned and state-holding enterprises, and domestic-funded enterprises. Large enterprises should learn from medium-sized enterprises, reduce the constraints on innovators through adopting relatively looser innovation policy, and simultaneously increase the returns to innovators. State-owned enterprises and state-holding enterprises should learn from private enterprises, change the rigid innovation system and innovation policy and establish a rational innovation incentive mechanism to mobilize the enthusiasm for technological innovation. Domestic-funded enterprises should strengthen exchanges and cooperation with foreign-funded enterprises. In addition to learning advanced technologies from foreign-funded enterprises, they should learn advanced innovation concepts, innovation system and innovation policy, improve the innovation environment, and increase the inputs in innovation. Moreover, the government should increase public inputs in innovation to lower the threshold of innovation, create a good environment for innovation and stimulate the intrinsic motivation of enterprises for technological innovation so that enterprises can truly become the subject of R&D investment, innovation activities and the application of innovation achievements.

Although valuable, limitations of the adopted approach and opportunities for its further improvement relate to, for example, forecasting future developments and changes in various types of enterprises, improving the way variables are measured (Liu et al. 2017) and refining the classification of enterprises. Another aspect is complementing the findings with qualitative analysis to better understand the results and the determinants of efficiency.

## Notes

1. Available at: <http://ghs.ndrc.gov.cn/zttp/ghjd/quanwen/> accessed 20 Dec 2017.
2. Available at: <http://www.most.gov.cn/kjgh/> accessed 20 Dec 2017.
3. Available at: <http://www.most.cn/yw/201209/t20120924_96972.htm> accessed 20 Dec 2017.
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## Acknowledgements

Work on this article was supported by a grant from the National Social Science Foundation of China (No. 16CJL020).

*Conflict of interest statement*. None declared.

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