Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2019 Volume 25 Issue 6: 1097–1122
https://doi.org/10.3846/tede.2019.10552

APPLICATION OF A HYBRID METHOD IN DISASTER PREVENTION AND RELIEF EVALUATION

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Received 01 September 2018; accepted 11 May 2019

Abstract. The purpose of this study is to propose a hybrid method for disaster prevention and relief (DPR) evaluation for Taiwan. Through the hybrid method and evaluation results, the central and local governments of Taiwan could continuously improve and strengthen their DPR system. The main structure of the evaluation is based on the balanced scorecard (BSC), and 15 indicators are gathered from the literature on related issues. These indicators are further analyzed by data envelopment analysis (DEA) and the Malmquist productivity index (MPI) to assess the DPR efficiency of 13 administrative regions in Taiwan. The analysis shows that the DPR system in Taiwan might be improved in Yunlin and Hsinchu City, two administrative regions analyzed during the three stages and time frame studied. The indicators that most significantly affect DPR efficiency are the average number of people served by each government employee or teacher (L1), the supervision score of the Department of Medical Services (DMS) of the Ministry of Health and Welfare (I4), the number of licensed medical practitioners per 10.000 people (C1) and the number of social welfare workers per 10.000 people (C2). These indicators also reflect Taiwan's current shortages in DPR-related and medical personnel.

Keywords: disaster prevention and relief, balanced scorecard, data envelopment analysis, Malmquist productivity index.

JEL Classification: O47, C44, C61, H12.

Introduction

Taiwan is an island nation situated in the Western Pacific typhoon zone and the Pacific Rim seismic zone. Compounded by global climate change, the natural disasters (e.g., earthquakes and typhoons) occurring in this region are expected to be of greater diversity, of greater magnitude and of increasing frequency, and the derived compound disasters will affect Taiwan with increasing intensity. According to a report entitled Natural Disaster Hotspots: A Global Risk Analysis, jointly published by the World Bank, Columbia University and the Norwegian Geotechnical Institute, Taiwan faces threats from three types of natural disasters,

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namely, earthquakes, droughts and typhoons, and Taiwan may become the most vulnerable region in the world. In Taiwan, approximately 73% of the land area and the population are exposed to three or more natural disaster risk factors (Dilley, Chen, Deichmann, Lerner-Lam, & Arnold, 2005).

Since 1999, Taiwan has repeatedly encountered earthquakes and typhoons that have caused severe damage. Although the capabilities and efficiency of DPR services have improved considerably, the number of casualties and the amount of property loss suggest that further improvements in the DPR system are possible. After studying the DPR systems of various countries, many experts have noted that the main problem facing Taiwan's current DPR system is the excessive division of DPR services, which has resulted in an inordinately large number of parties responsible for DPR. Consequently, the central government agencies are unable to effectively coordinate efforts with organizations on the same level as well as with those on the local level. Moreover, the local governments are incapable of efficiently cooperating with the central government agencies to implement plans for DPR and to take specific actions when disasters occur due to a lack of workforce and material resources and the inadequate capabilities of the DPR personnel. However, improvements require not only significant capital investment but also, more importantly, sufficient time to amass DPR materials and equipment and train professional DPR personnel. Therefore, the most urgent task in improving Taiwan's capacity to prevent disasters and provide disaster relief is to enhance the current DPR system and strengthen the overall capacity of the various agencies in the DPR system to cooperate and, thus, develop an improved, more effective DPR system.

To improve Taiwan's capacity to prevent and respond to disasters, Taiwan's National Science and Technology Center for Disaster Reduction (NCDR) has proposed a concept that uses the balanced scorecard (BSC) to evaluate the DPR performance of Taiwan's government agencies. The BSC can be used to integrate the mid- and long-term goals and strategies of an organization and convert them to specific action indicators. The goal is to address the lack of integrity, continuity and consistency in the current evaluation mechanism, reduce the waste of DPR resources and strengthen the current DPR system. However, this program is only in the conceptual phase, so a framework, indicators and applications have not yet been identified. This study proposes a concept that uses the balanced scorecard (BSC) to evaluate the DPR performance of Taiwan's government agencies. In this study, a concrete BSC framework and indicators for evaluating the DPR performance of Taiwan's government agencies are developed after reviewing the related literature and reports of the Central Disaster Prevention and Response Council. In addition, a DPR performance evaluation model is developed and evaluated by means of data envelopment analysis (DEA) in conjunction with the Malmquist productivity index (MPI). Based on the analysis, specific suggestions for policies to improve the DPR system of Taiwan's central and local governments are provided.

1. Literature review

1.1. Balanced scorecard (BSC)

Since Kaplan and Norton (1992) developed and popularized the BSC, it has been extensively used in academic circles and by various types of for-profit and nonprofit organizations. The BSC is an effective tool for evaluating the performance of organizations and a powerful

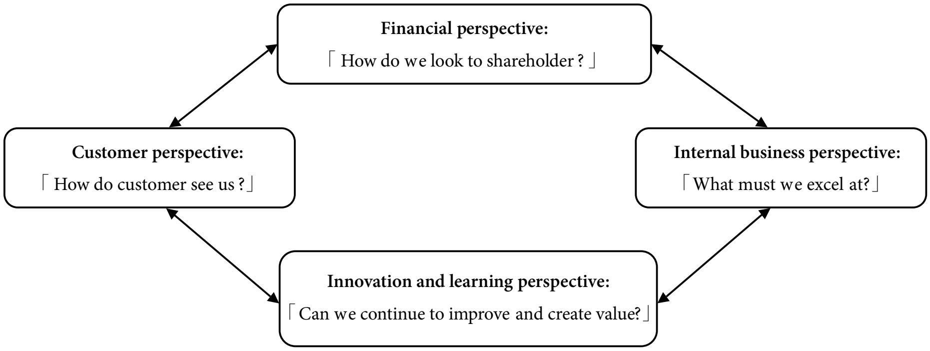

Figure 1. Main framework and essence of the BSC (source: compiled by the authors)

method that organizations can use to formulate various management-related strategies (Kaplan & Norton, 1992, 1996, 2000, 2004, 2006). The main function of the BSC is to integrate the mid- and long-term goals and strategies of an organization, convert them to specific action indicators and provide a framework composed of the aforementioned four perspectives (financial, customer, internal business process and learning and growth). Kaplan and Norton (1996) noted that the BSC has four main perspectives: financial, customer, internal business process and learning and growth. Figure 1 shows the framework of the BSC.

This section begins with a discussion on the basics of each perspective of the BSC, followed by the methodology proposed by the NCDR for applying the BSC in DPR evaluations and the evaluation indicators selected in this study.

1.1.1. Financial perspective

The financial measures in the BSC indicate the financial performance of an organization from the stakeholder perspective. The measures include increasing revenue, improving productivity, reducing costs, increasing the asset utilization ratio and risk management. These measures also indicate whether the implementation of the organization's strategies has made substantial contributions to increasing its profits. Because an organization will seek financial goals congruent with its stage of development (i.e., business lifecycle), the financial perspective can be roughly divided into three stages: growth, sustain and harvest. Thus, the purpose of the financial perspective is to identify how an organization should appear to its stakeholders to secure investments. According to the NCDR, the objectives of the financial perspective are to increase income, reduce expenditures, effectively use funds and appropriately allocate and spend DPR funds. In this study, three indicators were selected for the financial perspective: general administrative expenditures, social welfare expenditures and police service expenditures (Table 1).

Table 1. Financial perspective indicators (source: compiled by the authors)

Perspective	Indicator (Code)
Financial	General administrative expenditures (F1)
	Social welfare expenditures (F2)
	Police service expenditures (F3)

1.1.2. Customer perspective

The customer measures in the BSC determine how customers view an organization. The customer perspective focuses on measures such as customer satisfaction, customer retention, customer profitability and market and customer share. Therefore, the purpose of the customer perspective is to identify how an organization should approach its customers to realize its vision. According to the NCDR, the objectives of the customer perspective are to establish excellent performance management, expand DPR resources and capacity and, consequently, reduce the effects of disasters and address the current demand for DPR services. Currently, Taiwan has severe shortages in DPR-related (e.g., police and firefighting) personnel and equipment. Therefore, addressing the shortages in workforce and material resources is an important task for current DPR services and government agencies at various levels. In this study, three indicators were selected for the customer perspective: the average number of licensed medical practitioners per 10.000 people, the average number of social welfare workers per 10.000 people and the average number of firefighters per 10.000 people (Table 2).

Table 2. Customer perspective indicators (source: compiled by the authors)

Perspective	Indicator (Code)
Customer	The average number of licensed medical practitioners per 10.000 people (C1)
	The average number of social welfare workers per 10.000 people (C2)
	The average number of firefighters per 10.000 people (C3)

1.1.3. Internal business process perspective

The internal business process measures in the BSC reflect the areas in which an organization must possess special skills that will improve the core work flow and customer satisfaction and enable the achievement of financial goals, thereby allowing the organization to attract and retain customers in the target market and meet the stakeholders' expectations of financial reward. Therefore, the purpose of the internal business process perspective is to identify which operational procedures an organization should adopt to satisfy its customers and stakeholders. According to the NCDR, the objectives of the internal business process perspective are to improve efficiency and stimulate organizational updates. Since 2003, Taiwan's central authorities responsible for DPR have conducted annual reviews of the local governments to evaluate and supervise DPR-related tasks. Therefore, based on the relevant literature and the supervision scores of DPR-related departments, six indicators were selected in this study to evaluate the internal business process: the supervision score of the National Police Agency (NPA), the supervision score of the National Fire Agency (NFA), the supervision score of the Ministry of Economic Affairs (MEA), the supervision score of the Department of Medical Services (DMS) of the Ministry of Health and Welfare, the supervision score of the Department of Social Assistance and Social Work (DSASW) of the Ministry of Health and Welfare and the supervision score of the NCDR (Table 3).

Table 3. Internal business process perspective indicators (source: compiled by the authors)

Perspective	Indicator (Code)
Internal/Business Process	The supervision score of the National Police Agency (NPA) (I1)
	The supervision score of the National Fire Agency (NFA) (I2)
	The supervision score of the Ministry of Economic Affairs (MEA) (I3)
	The supervision score of the Department of Medical Services (DMS) of the Ministry of Health and Welfare (I4)
	The supervision score of the Department of Social Assistance and Social Work (DSASW) of the Ministry of Health and Welfare (I5)
	The supervision score of the NCDR (I6)

Note: NCDR National Science and Technology Center for Disaster Reduction.

1.1.4. Learning and growth perspective

The learning and growth measures in the BSC examine the ability of an organization to maintain its long-term advantages, focusing on the capabilities of the employees of the organization to adjust, learn, grow and innovate in areas such as technological reconstruction, information technology and systems, organizational procedures and day-to-day operations. The purpose of the learning and growth perspective is to identify how an organization can ensure continuous change and improvement to realize its vision. According to the NCDR, the objectives of the learning and growth perspective are to improve workforce quality and encourage innovation. Therefore, the most important aspect of learning and growth is to improve the capacity of the local government employees responsible for DPR. In this study, three indicators were selected to evaluate the learning and growth perspective: the average number of people served by each government employee or teacher, the number of government employees and teachers with a college degree or higher and the supervision score of the Department of Civil Affairs (DCA) (Table 4).

Table 4. Learning and growth perspective indicators (source: compiled by the authors)

Perspective	Indicator (Code)
Learning and Growth	The average number of people served by each government employee or teacher (L1)
	The number of government employees and teachers with a college degree or higher (L2)
	The supervision score of the Department of Civil Affairs (DCA) (L3)

Kaplan and Norton (1996) noted that because the BSC is a strategy development system, it should include not only a set of key indicators but also, more importantly, a set of consistent and connected indicators of the four perspectives (i.e., financial, customer, internal business process, and learning and growth) and the goals of the organization. For companies, one of the most commonly used financial perspective indicators is the return on capital employed (ROCE). The ROCE is determined primarily by customers' repeated purchases and the proceeds of sales, both of which result from high customer loyalty. However, to attain high customer loyalty, a company must ensure on-time delivery (OTD). To maintain consistent OTD, a company must improve its internal operating procedures and shorten its operating cycle. The key to a company improving its internal operating procedures is for it to develop and enhance employee skills and productivity.

Based on this logic, the cause-and-effect relationships between the financial, customer, internal business process, and learning and growth perspectives of the BSC can be established (Figure 2). Based on these cause-and-effect relationships, the DPR performance evaluation model developed in this study was divided into three stages, which are shown in Table 5.

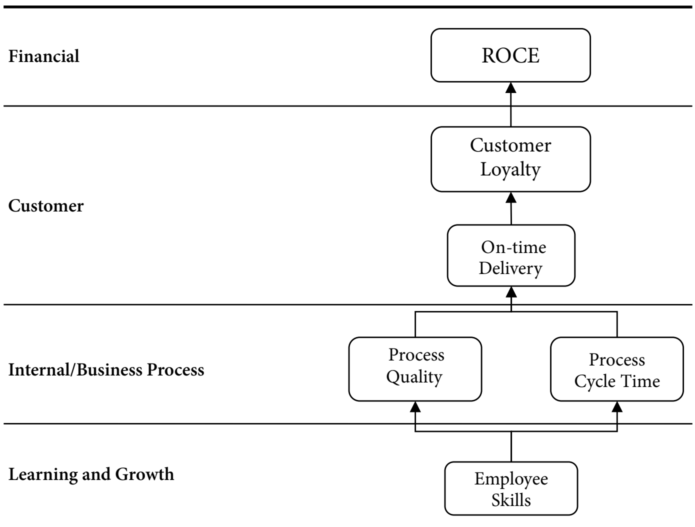

Figure 2. The cause-and-effect relationship between the four perspectives of the BSC (source: compiled by the authors)
Note: ROCE Return on Capital Employed.

Table 5. Analysis stages (source: compiled by the authors)

Analysis stage	Input	Output
Stage I	Learning and Growth	Internal/Business Process
Stage II	Internal/Business Process	Customer
Stage III	Customer	Financial

1.2. Data envelopment analysis (DEA)

DEA, which was developed by Charnes, Cooper, and Rhodes (1978) as an extension of the concept of the production frontier proposed by Farrell (1957) to evaluate efficiency, is a productivity evaluation method that can be used to evaluate multi-input and multioutput systems and decision-making units (DMUs) (Golany & Roll, 1989). DEA is one of many efficiency analysis and performance evaluation tools. DEA evaluates the efficiency frontier and the relative efficiency of DMUs. The model proposed by Charnes et al. (1978) (CCR model) is as follows:

$$\text{Max } h_i = \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}}; \tag{1}$$

$$\text{st. } h_i = \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \le 1;$$

$$u_r, v_i \ge \varepsilon > 0;\ r = 1,\ldots,s;\ i = 1,\ldots,m;\ r = 1,\ldots,s;\ j = 1,\ldots,n,$$

where Y_{rj} is the output quantity of the r^{th} item of the j^{th} DMU, X_{ij} is the input quantity of the i^{th} item of the j^{th} DMU, and ε, referred to as the non-Archimedean number by Charnes et al. (1978), is a positive number, where the value is often set to 10^{-4} or 10^{-6} in practice.

Because the CCR model evaluates the overall efficiency under the assumption of constant returns to scale (CRS) and inefficiency may be, partially, a result of the operational scale, Banker, Charnes, and Cooper (1984) developed the BCC model:

$$\text{Max } h_i = \frac{\sum_{r=1}^{s} u_r Y_{rj} - u_0}{\sum_{i=1}^{m} v_i X_{ij}}; \tag{2}$$

$$\text{st. } h_i = \frac{\sum_{r=1}^{s} u_r Y_{rj} - u_0}{\sum_{i=1}^{m} v_i X_{ij}} \le 1;$$

$$u_r, v_i \ge \varepsilon > 0;\ r = 1,\ldots,s;\ i = 1,\ldots,m;\ j = 1,\ldots,n.$$

Compared with the CCR model, the BCC model contains an additional variable, u_0, which represents the trend of the returns to scale:

- $u_0 < 0$ represents increasing returns to scale;
- $u_0 = 0$ represents CRS; and
- $u_0 > 0$ represents decreasing returns to scale.

In terms of the BSC, other than the NCDR of Taiwan proposing the concept of using the BSC for DPR evaluation, only Moe, Gehbauer, Senitz, and Mueller (2007) have studied the importance and necessity of using the BSC to effectively manage natural disaster projects and have successfully applied the BSC for a real flood disaster management project in Thailand. In addition to other applications, Shen, Chen, and Wang (2016) used the BSC for enterprise resource planning (ERP) system performance measurement, and the result showed that the BSC could enhance the effectiveness at the postimplementation stage under evaluators' subjective, uncertainty, and vagueness judgments. Lu, Hsu, Liou, and Lo (2018) adapted the BSC as their research model and used multiple-criteria decision making (MCDM) to establish a sustainable performance evaluation for international airports, and the results showed that it could generate more detailed and reliable results through the BSC. Mehralian, Nazari, Nooriparto, and Rasekh (2017) used the BSC to examine the relationship between the implementation of total quality management (TQM), and the result showed that TQM implementation was positively and significantly influenced by the BSC.

Therefore, the BSC could not only enhance the effectiveness of TQM implementation but also help managers reach their goals and strategic objectives. Hu, Leopold-Wildburger, and Strohhecker (2017) designed a strategy implementation map using the BSC and found that the BSC provided the most focused and useful information in support of participants when carrying out the tasks. Singh, Olugu, Musa, and Mahat (2018) used the BSC to evaluate the sustainability of manufacturing small and medium-sized enterprises (SMEs), and the results showed that the BSC could help the managers of larger enterprises assess the effectiveness of their sustainability strategies. Regarding DEA, Üstün and Barbarosoğlu (2015) used it to estimate the relative efficiency of disaster relief organizations following the Marmara and Düzce earthquakes in Turkey in 1999. Üstün (2016) used DEA to evaluate the disaster resilience capacity to earthquakes in 30 districts in İstanbul. Cheng and Chang (2018) combined the geographic information system (GIS) and DEA to address the prioritization problem by calculating policy efficiency. Another application of DEA related to DPR is vulnerability analysis; Zou and Wei (2009) used DEA to assess the performance of coastal hazards from 1995 to 2005 in eight Southeast Asian countries. Saein and Saen (2012) used seismotectonic and geotechnical data and DEA to calculate the vulnerability efficiency of 20 districts in Iran. There were serious analyses using DEA on the vulnerability to natural disasters focused in China; Wei, Fan, Lu, and Tsai (2004) collected annual governmental statistics from 1898 to 2000 and used DEA to evaluate the performance of regional vulnerability to natural disasters in 17 regions in China from 2001 to 2010. Huang, Liu, and Ma (2011) used DEA to assess the regional vulnerability to natural hazards of 31 assessment units, including 22 provinces, 5 autonomous regions and 4 municipalities in China. Huang et al. (2012) used DEA to assess the multidimensional flood vulnerability of 31 provinces in China from 2001 to 2010. Yuan et al. (2015) used DEA to evaluate the performance of vulnerability to drought and proposed mitigation strategies according to the results of the analysis.

In regard to integrating BSC-DEA models for DPR studies, however, there is currently no study on the topic. The integrated BSC-DEA methods have been widely recommended and employed in various research fields and organizations (Aryanezhad, Najafi, & Farkoosh, 2011; Amado, Santos, & Marques, 2012; Fletcher & Brannigan, 2004; Eilat, Golany, & Shtub, 2008; Kádárová, Durkáčová, Teplická, & Kádár, 2015; Kartalis, Velentzas, & Broni, 2013). Amado et al. (2012) evaluated the performance of the equipment maintenance departments of 15 manufacturers using an integrated BSC-DEA approach. It was found that their financial performance could be improved to fulfill the requirements of the shareholders by determining the internal process that provided the most value from the learning and growth perspective of the BSC. The result was an understanding of the relationship between this process and the customers. Paramanik and Kar (2013) simulated the performance of a company in implementing sustainable technologies using an integrated BSC-DEA approach and noted that, by means of an integrated BSC-DEA approach, a company could not only compare its sustainable technologies with those of other companies but also understand the effects of the four perspectives of the BSC on its operations and sustainability measures. Sadeghani, Mollaverdi, Shirouyehzad, and Jafarpour (2013) noted that performance evaluations and innovation are considered major sources of competitive advantage, and the BSC is an effective tool for evaluating R&D. Thus, they evaluated 50 R&D plans using the BSC in combination with DEA and found that the integrated BSC-DEA model was capable of effectively determining the efficiency and feasibility of an R&D plan. In a literature review, Shafiee, Lotfi, and Saleh (2014) used the integrated BSC-DEA approach to evaluate the supply chain performance of 20 food suppliers in Iran. They found that the integrated BSC-DEA approach was capable of evaluating both financial and nonfinancial performance and that the effectiveness, efficiency and balance goals could be achieved by means of this combined method. Haghighi, Torabi, and Ghasemi (2016) proposed the BSC-DEA framework to evaluate the performance of a sustainable supply chain. The study used the BSC to classify a more comprehensive and thorough understanding of sustainability strategies, and then, DEA was capable of dealing with both qualitative and quantitative dates to compute efficiency scores and find the benchmarked unit at each echelon. Mostafaeipour, Qolipour, and Mohammadi (2016) and Qolipour et al. (2016) used an integrated approach composed of DEA, the BSC and game theory (GT) to evaluate the performance of photovoltaic plants and wind power generation potential in provinces of Iran. Both studies found that the integrated approach of the BSC and DEA has better accuracy and ability to properly detect the relationships between the decision-making components than the simple DEA method. Wang and Chien (2016) proposed the BSC-DEA framework to diagnose 23 light-emitting diode (LED) manufacturers in Taiwan and indicated that the BSC-DEA framework could provide managerial insights to make an adaptive adjustment to significant KPIs (key performance indicators). Bazrkar and Iranzadeh (2017) used the BSC and DEA to build a strategic process to allow banks to apply lean Six Sigma properly and avoid bias from self-assessment or evaluation in the best condition. Sun, Yu, Tan, Xu, and Yun (2017) applied interpretive structural modeling (ISM), principal component analysis (PCA), the BSC and DEA to evaluate 14 provincial companies, and the results showed that DEA could better reflect the time lag of the grid enterprises' operating investment and income. Moreover, the analysis results of DEA had stronger rationality and consistency with the factual data. Tan, Zhang, and Khodaverdi (2017) used DEA and the BSC to evaluate and measure the service performance of 10 automobile dealers and indicated that analysis results of DEA and the BSC could provide automobile dealers with specific perspectives and data for improving their service performance. Basso, Casarin, and Funari (2018) integrated DEA with the BSC to measure the performance of museums; the study set the BSC to devise the multidimensional nature of the museum as the first stage. In the second stage, DEA was used to compute the efficiency scores of each BSC perspective. Dolasinski, Reborts, and Zheng (2019) used the BSC and DEA to measure the efficiency of 54 hotel distribution channel mixes in the United States and indicated that the integrated approach of DEA and the BSC provided not only a new way to identify individual performance but also a reference set of benchmarks for improvement based on the relationship between individual hotels and their referent efficient hotels.

Therefore, previous studies applying the BSC and DEA to natural disaster and vulnerability management-related issues showed that the BSC and DEA are both practical methods for evaluating disaster prevention and relief. The BSC could provide decision makers with clear goals and objectives and identify where the problem is (Kaplan & Norton, 1992, 1996, 2000, 2004, 2006; Moe, Gehbauer, Senitz, & Mueller, 2007; Lotfi, Sadjadi, Khaki, & Najafi, 2010). DEA could not only evaluate efficiency with concrete measurements but also indicate and rank inefficient DMUs and provide specific improvement figures, benchmarks (Charnes et al., 1978; Banker et al., 1984; Cook & Seiford, 2009; Emrouznejad & Yang, 2018). However, there is no study on the benefit of integrating BSC-DEA models into DPR practices or on their application. In terms of Taiwan, the BSC could improve the problems of discoordination of DPR divisions and governments at different levels, and DEA could indicate concrete optimal resource allocation during the period of a lack of workforce and material resources and inadequate capabilities of the DPR personnel. Essentially, this study applies BSC-DEA models to DPR not only to extend the concept proposed by the NCDR but also to take further steps to propose an implementation for the urgent need for improvements in the DPR system of Taiwan. Moreover, this study also used sensitivity analysis to observe the effect of input on efficiency (Charnes & Neralic, 1990; Neralic, 1997). The purpose of the sensitivity analysis was to let the DPR decision makers identify the importance of inputs to the DPR performance and make the proper adjustments for resource allocation. While important inputs must not necessarily be reduced in DPR, DPR decision makers could transform the redundant inputs into other actions under the premise of policy licensing. Such a transformation is an urgent need of Taiwan's DPR system and one of the main contributions of the research.

1.3. Malmquist productivity index (MPI)

The main objective of the BSC is to integrate the mid- and long-term goals and strategies of an organization and convert them into specific actions. In comparison, although DEA is capable of analyzing the performance of DMUs at various times, it is incapable of analyzing the performance of DMUs over multiple periods, which a company can use as a basis to create long-term strategies. To address this problem, the MPI was also measured in this study (Ahn & Min, 2014; Kaplan & Norton, 1996; Milis & Mercken, 2004; De Nicola, Gitto, & Mancuso, 2013). The MPI was proposed by Caves, Christensen, and Diewert (1982) and is based on the distance function used by Malmquist (1953) and Shephard (1970). Färe, Grosskopf, Norris, and Zhang (1994) evaluated efficiency under CRS conditions based on the geometric mean, improved the model proposed by Caves et al. (1982) and subsequently proposed a new measure, total factor productivity (TFP):

$$\mathrm{TFP}\left(x^{t+1}, y^{t+1}, x^{t}, y^{t} \middle| \mathrm{CRS}\right) = \left[\frac{D_0^t\left(x^{t+1}, y^{t+1} \middle| \mathrm{CRS}\right) D_0^{t+1}\left(x^{t+1}, y^{t+1} \middle| \mathrm{CRS}\right)}{D_0^t\left(x^{t}, y^{t} \middle| \mathrm{CRS}\right) D_0^{t+1}\left(x^{t}, y^{t} \middle| \mathrm{CRS}\right)}\right]^{\frac{1}{2}} = \quad (3)$$

$$\left[\frac{D_0^t\left(x^{t+1}, y^{t+1} \middle| \mathrm{CRS}\right) D_0^t\left(x^{t}, y^{t} \middle| \mathrm{CRS}\right)}{\mathrm{D}_0^t\left(x^{t+1}, y^{t+1} \middle| \mathrm{CRS}\right) D_0^{t+1}\left(x^{t}, y^{t} \middle| \mathrm{CRS}\right)}\right]^{\frac{1}{2}} \times \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1} \middle| \mathrm{CRS}\right)}{D_0^t\left(x^{t}, y^{t} \middle| \mathrm{CRS}\right)} = \quad (4)$$

technical change (TC) × (technical change efficiency; EC).

Because the MPI is a measure of the performance of DMUs over multiple periods, it is often used in combination with DEA. Qazi and Yulin (2012) measured the productivity of 15 high-tech industries in China between 2000 and 2010 using DEA and the MPI to find an increase in the productivity of two of the 15 high-tech industries, namely, the electronic component and office equipment industries. Based on the safety performance evaluation indicators proposed by the European Transport Safety Council, Egilmeza and McAvoy (2013) analyzed road safety in the U.S. between 2002 and 2008 using DEA and the MPI and found that investment in road safety systems was the most important factor in reducing fatal accidents. De Nicola et al. (2013) analyzed the quality of service and the productivity of Italian airports between 2006 and 2008 using the MPI in combination with DEA. An important advancement in this study was to include data on the quality of service. Based on the analysis, the authors provided specific suggestions for improving airport quality of service. In view of the increasing varieties of services provided by airports, Ahn and Min (2014) studied the operational performance of 23 international airports between 2006 and 2011 using DEA in combination with the MPI and found that the performance of international airports was significantly affected by government policies and technological advances. Örkcü, Balıkçı, Dogan, and Genç (2016) used DEA and the MPI to assess the operational efficiency and productivity of 21 Turkish airports during the period of 2009 to 2014. Maroto and Zofí (2016) used DEA and the MPI to measure the accessibility of road transport infrastructure during the period 1995 to 2005 in Spain. Kamarudin, Hue, Sufían, and Anwar (2017) used DEA and the MPI to evaluate the level of productivity of 29 Islamic banks from Southeast Asian countries, namely, Brunei, Indonesia and Malaysia. Falavigna, Ippoliti, and Ramello (2018) used DEA in combination with the MPI to evaluate the productivity of tax judiciary in Italy and then examined the impact of the policy on improving judicial productivity. Khalili and Alinezhad (2018) used the BSC, DEA and the MPI to analyze and investigate the efficiency of the green supply chain of 15 manufacturing firms in Iran. The results indicated that the proposed model had a high degree of accuracy and interpretation in evaluating performance and helped managers and experts make better decisions.

For more than 10 years, the central government authorities responsible for DPR in Taiwan have conducted annual evaluations of counties and cities concerning DPR performance. In this study, we used the MPI in combination with the BSC and DEA to evaluate the long-term results of the DPR efforts of the central and local authorities. This evaluation could make the research more comprehensive and be further used by the central and local authorities to formulate DPR-related long-term strategies.

2. Method application and results

2.1. Analysis indicators

Tables A1 to A3 summarize the indicator raw data of 13 administrative regions from 2015 to 2017, corresponding to the four perspectives (i.e., financial, customer, internal business process and learning and growth) of the BSC, determined based on an analysis of the data relevant to DPR in Taiwan. The data sources of the indicators of the research were collected from the National Statistics, R.O.C. (Taiwan) and the Central Disaster Prevention and Response Council.

2.2. Decision-making units (DMUs)

Originally, a total of 22 administrative regions, including direct-controlled municipalities, cities and counties, were initially selected as the DMUs to be analyzed. Certain regions were rejected because of insufficient data, so 13 administrative regions were ultimately selected as DMUs in this study (Table 6).

Table 6. Administrative regions of Taiwan (source: compiled by the authors)

Administrative region	Name
Municipality	Taoyuan, Kaohsiung
City	Keelung, Hsinchu, Chiayi
County	Hsinchu, Miaoli, Nantou, Yunlin, Chiayi, Yilan, Hualien, Taitung

2.3. Efficiency and productivity analysis

2.3.1. Stage I: learning and growth – internal business process

Table 7 summarizes the stage I analysis results. As demonstrated in Table 7, at stage I, in 2015, Taoyuan, Yunlin and Hualien were the only three administrative regions rated as inefficient, whereas the other 10 administrative regions were rated as efficient. The inefficiency of Taoyuan and Hualien was caused by both technical and scale inefficiency, while the inefficiency of Yunlin was caused by only scale inefficiency. In 2016, eight administrative regions, namely, Yilan, Hsinchu County, Yunlin, Chiayi County, Taitung, Keelung, Hsinchu City and Chiayi City, were rated as efficient. The other five administrative regions, Kaohsiung, Taoyuan, Miaoli, Nantou and Hualien, were rated as inefficient. The inefficiency of Kaohsiung and Miaoli was caused by both technical and scale inefficiency, while the inefficiency of Taoyuan, Nantou and Hualien was caused by only technical inefficiency. In 2017, eight administrative regions, namely, Kaohsiung, Yilan, Hsinchu County, Miaoli, Taitung, Keelung, Hsinchu City and Chiayi City, were rated as efficient. The other five administrative regions, namely, Taoyuan,

Table 7. Stage 1 efficiency analysis results (source: compiled by the authors)

Administrative region	2015			2016			2017		
	CCR	BCC	SCE	CCR	BCC	SCE	CCR	BCC	SCE
Kaohsiung	1	1	1	0.6105	0.7895	0.7733	1	1	1
Taoyuan	0.7075	0.9318	0.7593	0.5000	0.5000	1	0.5000	0.5000	1
Yilan	1	1	1	1	1	1	1	1	1
Hsinchu(cou)	1	1	1	1	1	1	1	1	1
Miaoli	1	1	1	0.4654	0.7500	0.6205	1	1	1
Nantou	1	1	1	0.7500	0.7500	1	0.5000	0.5000	1
Yunlin	0.8173	1	0.8173	1	1	1	0.7738	0.9706	0.7972
Chiayi(cou)	1	1	1	1	1	1	0.6437	0.6966	0.9241
Taitung	1	1	1	1	1	1	1	1	1
Hualien	0.5332	0.5453	0.9778	0.5000	0.5000	1	0.4016	0.4233	0.9487
Keelung	1	1	1	1	1	1	1	1	1
Hsinchu(cit)	1	1	1	1	1	1	1	1	1
Chiayi(cit)	1	1	1	1	1	1	1	1	1
Av*	0.9275	0.9598	0.9657	0.8328	0.8684	0.9534	0.8322	0.8531	0.9746

Note: Av* Average, cou County, cit City, CCR overall efficiency, BCC technical efficiency, SCE scale efficiency.

Nantou, Yunlin, Chiayi County and Hualien, were rated as inefficient. The inefficiency of Yunlin, Chiayi County and Hualien was caused by both technical and scale inefficiency, while the inefficiency of Taoyuan and Nantou was caused by only technical inefficiency. As a whole, in the three years from 2015 to 2017, the inefficiency of the DPR agencies in Taiwan was mainly due to lower technical inefficiency.

As demonstrated by the stage I productivity analysis results shown in Table 8, six administrative regions, namely, Kaohsiung, Yunlin, Taitung, Hualien, Hsinchu City and Chiayi City, were rated as having productivity growth. Among the six administrative regions, the productivity growth of Kaohsiung, Yunlin, Taitung, Hualien, Hsinchu City and Chiayi City was caused by the growth of TC, while the EC of Yunlin and Hualien declined. The other six administrative regions, namely, Taoyuan, Yilan, Miaoli, Nantou, Chiayi County and Keelung, were rated as having productivity decline. Among the six administrative regions, the productivity decline of Yilan, Miaoli, and Keelung was caused by the decline of TC, while the productivity decline of Taoyuan and Chiayi County was caused by the decline of both TC and EC. Among the 13 administrative regions, Hsinchu County was the only administrative region that constantly exhibited productivity in each MPI indicator. As a whole, in the three years from 2015 to 2017, the productivity decline of the DPR agencies in Taiwan was mainly due to the decline of EC.

Table 9 summarizes the stage I sensitivity analysis results. As demonstrated in Table 10, the average number of people served by each government employee or teacher (L1) had the most significant effect on the overall efficiency (if this indicator is ignored, the efficiency decreases from 0.8642 to 0.8087), followed by the supervision score of the DCA (L3) and the number of government employees and teachers with a college degree or higher (L2).

Table 8. Stage 1 MPI analysis results (2015–2017) (source: compiled by the authors)

Administrative region	TFP	TC	EC
Kaohsiung	1.089	1.098	1
Taoyuan	0.829	0.986	0.841
Yilan	0.988	0.988	1
Hsinchu(cou)	1	1	1
Miaoli	0.890	0.890	1
Nantou	0.735	1.040	0.707
Yunlin	1.025	1.053	0.973
Chiayi(cou)	0.622	0.775	0.802
Taitung	1.122	1.122	1
Hualien	1.050	1.016	0.990
Keelung	0.857	0.857	1
Hsinchu(cit)	1.069	1.069	1
Chiayi(cit)	1.207	1.207	1
Av*	0.943	1.001	0.942

Note: Av* Average, cou County, cit City, TFP total factor productivity, TC technical change, EC technical change efficiency.

Table 9. Stage 1 sensitivity analysis results (source: compiled by the authors)

Year	All inputs	Ignored (L1)	Ignored (L2)	Ignored (L3)
2015	0.9275	0.8432	0.9025	0.9110
2016	0.8328	0.7776	0.8283	0.7752
2017	0.8322	0.8053	0.8186	0.7872
Av*	0.8642	0.8087	0.8498	0.8245
Influence order: L1 > L3 > L2				

Note: Av* Average, F1 General administrative expenditures, F2 Social welfare expenditures, F3 Police service expenditures.

2.3.2. Stage II: internal business process – customer

Table 10 summarizes the stage II efficiency analysis results. As demonstrated in Table 10, in 2015, eight administrative regions, namely, Miaoli, Nantou, Chiayi County, Taitung, Hualien, Keelung, Hsinchu City and Chiayi City, were rated as efficient. The other five administrative regions, namely, Kaohsiung, Taoyuan, Yilan, Hsinchu County and Yulin, were rated as inefficient. The inefficiency of Taoyuan, Yilan, Hsinchu County and Yunlin was caused by technical inefficiency, while the inefficiency of Kaohsiung was caused by both technical and scale inefficiency. In 2016, eight administrative regions, namely, Kaohsiung, Taoyuan, Nantou, Yunlin, Chiayi County, Hualien, Hsinchu City and Chiayi City, were rated as efficient. The other five administrative regions, namely, Yilan, Hsinchu County, Miaoli, Taitung and Keelung, were rated as inefficient. Among the five administrative regions, the inefficiency

Table 10. Stage 2 efficiency analysis results (source: compiled by the authors)

Administrative region	2015			2016			2017		
	CCR	BCC	SCE	CCR	BCC	SCE	CCR	BCC	SCE
Kaohsiung	0.4903	0.9161	0.5352	1	1	1	1	1	1
Taoyuan	0.7553	0.7553	1	1	1	1	1	1	1
Yilan	0.7721	0.7721	1	0.8735	0.8735	1	0.7582	0.7582	1
Hsinchu(cou)	0.8646	0.8646	1	0.8767	0.8767	1	0.8220	0.8220	1
Miaoli	1	1	1	0.9233	0.9233	1	0.9113	0.9113	1
Nantou	1	1	1	1	1	1	0.9314	0.9314	1
Yunlin	0.7437	0.7437	1	1	1	1	1	1	1
Chiayi(cou)	1	1	1	1	1	1	1	1	1
Taitung	1	1	1	0.8945	1	0.8945	0.8063	1	0.8063
Hualien	1	1	1	1	1	1	1	1	1
Keelung	1	1	1	0.9699	0.9800	0.9897	0.8075	0.8075	1
Hsinchu(cit)	1	1	1	1	1	1	0.9192	0.9112	1
Chiayi(cit)	1	1	1	1	1	1	1	1	1
Av*	0.8943	0.9721	0.9642	0.9645	0.9733	0.9911	0.9197	0.9340	0.9858

Note: Av* Average, cou County, cit City, CCR overall efficiency, BCC technical efficiency, SCE scale efficiency.

of Yilan, Hsinchu County and Miaoli was caused by technical inefficiency, whereas the inefficiency of Taitung was caused by only scale inefficiency. Keelung was the only administrative region in which the inefficiency was caused by both technical and scale inefficiency. In 2017, six administrative regions, namely, Kaohsiung, Taoyuan, Yunlin, Chiayi County, Hualien and Chiayi City, were rated as efficient. The other seven administrative regions, namely, Yilan, Hsinchu County, Miaoli, Nantou, Taitung, Keelung and Hsinchu City, were rated as inefficient. Among the seven administrative regions, the inefficiency of Yilan, Hsinchu County, Miaoli, Nantou, Keelung and Hsinchu City was caused by technical inefficiency, whereas the inefficiency of Taitung was caused by scale inefficiency. The inefficiency of the DPR agencies was mainly due to the lower technical inefficiency during these three years.

Table 11 shows the stage II MPI analysis results. As demonstrated in Table 11, among the 13 administrative regions, 11 administrative regions, namely, Kaohsiung, Taoyuan, Yilan, Miaoli, Nantou, Yunlin, Chiayi County, Hualien, Keelung, Hsinchu City and Chiayi City, were rated as having productivity growth. Of the six administrative regions, namely, Kaohsiung, Taoyuan, Miaoli, Yunlin, Chiayi County and Hsinchu City, productivity growth was caused by the growth of both TC and EC. The productivity growth of Yilan, Nantou, Hualien, Keelung, and Chiayi City was caused by the growth of TC, while the EC of Yilan, Nantou and Keelung declined. Two administrative regions, namely, Hsinchu County and Taitung, were rated as having productivity decline, and the decline in Hsinchu County was caused by the decline of EC, while the decline in Taitung was caused by the decline of both TC and EC. Overall, the DPR agencies exhibited growth in each MPI indicator only in stage II during these three years.

Table 11. Stage 2 MPI indicator analysis results (2015–2017) (source: compiled by the authors)

Administrative region	TFP	TC	EC
Kaohsiung	1.748	1.194	1.464
Taoyuan	1.576	1.370	1.151
Yilan	1.166	1.177	0.991
Hsinchu(cou)	0.997	1.023	0.975
Miaoli	1.044	1.036	1.008
Nantou	1.149	1.170	0.982
Yunlin	1.559	1.344	1.160
Chiayi(cou)	1.555	1.544	1.007
Taitung	0.881	0.981	0.898
Hualien	1.112	1.112	1
Keelung	1.038	1.156	0.898
Hsinchu(cit)	1.273	1.238	1.028
Chiayi(cit)	1.011	1.011	1
Av*	1.212	1.171	1.035

Note: Av* Average, cou County, cit City, TFP total factor productivity, TC technical change, EC technical change efficiency.

As demonstrated by the sensitivity analysis results shown in Table 12, the supervision score of the Department of Medical Services (DMS) of the Ministry of Health and Welfare (I4) had the greatest effect on the overall efficiency (if this indicator is ignored, the efficiency decreases from 0.9262 to 0.9093), followed by the supervision score of the NPA (I1), the supervision score of the DSASW (I5), the supervision score of the MEA (I3), and the supervision score of the NFA (I2). The supervision score of the NCDR (I6) had the least effect on the overall efficiency (if this indicator is ignored, the efficiency decreases from 0.9262 to 0.9247).

Table 12. Stage 2 sensitivity analysis results (source: compiled by the authors)

Year	All inputs	Ignored (I1)	Ignored (I2)	Ignored (I3)	Ignored (I4)	Ignored (I5)	Ignored (I6)
2015	0.8943	0.8571	0.8894	0.8837	0.8908	0.8882	0.8943
2016	0.9645	0.9645	0.9645	0.9568	0.9529	0.9551	0.9600
2017	0.9197	0.9070	0.9170	0.9197	0.8843	0.9083	0.9197
Av*	0.9262	0.9095	0.9236	0.9201	0.9093	0.9172	0.9247
Influence order: I4 > I1 > I5 > I3 > I2 > I6							

Note: Av* Average, I1 the supervision score of the National Police Agency (NPA), I2 the supervision score of the National Fire Agency (NFA), I3 the supervision score of the Ministry of Economic Affairs (MEA), I5 the supervision score of the Department of Social Assistance and Social Work (DSASW) of the Ministry of Health and Welfare, I6 the supervision score of the NCDR.

2.3.3. Stage III: customer – financial

As demonstrated by the stage III efficiency analysis results shown in Table 13, in 2015, Kaohsiung was the only administrative region rated as efficient, whereas all the other administrative regions were rated as inefficient. Among the 12 inefficient administrative regions, the inefficiency of five administrative regions, Taoyuan, Yilan, Hsinchu County, Miaoli and Yunlin, was caused by scale inefficiency. The inefficiency of the other seven administrative regions, namely, Nantou, Chiayi County, Taitung, Hualien, Keelung, Hsinchu City and Chiayi City, was caused by both technical and scale inefficiency. The efficiency analysis results of 2016 were almost the same as those of 2015. Kaohsiung was still the only administrative region rated as efficient, but the inefficiency of Taoyuan was caused by both technical and scale inefficiency, instead of scale inefficiency, in 2015. In 2017, Kaohsiung and Yilan were the only two administrative regions rated as efficient, whereas the other 11 administrative regions were rated as inefficient. Among the other 11 administrative regions, the inefficiency of Hsinchu County and Yunlin was caused by scale inefficiency. The inefficiency of nine administrative regions, namely, Taoyuan, Miaoli, Nantou, Chiayi County, Taitung, Hualien, Keelung, Hsinchu City and Chiayi City, was caused by both technical and scale inefficiency. As a whole, the cause of the inefficiency ratings was due to the lower technical inefficiency, which is the same as in stage I and stage II.

As demonstrated by the stage III MPI analysis results shown in Table 14, of the 13 administrative regions, six administrative regions, namely, Taoyuan, Yilan, Hsinchu County, Nantou, Yunlin and Hsinchu County, were rated as having productivity growth. The productivity growth of five administrative regions, namely, Taoyuan, Yilan, Hsinchu County,

Table 13. Stage 3 efficiency analysis results (source: compiled by the authors)

Administrative region	2015			2016			2017		
	CCR	BCC	SCE	CCR	BCC	SCE	CCR	BCC	SCE
Kaohsiung	1	1	1	1	1	1	1	1	1
Taoyuan	0.2776	1	0.2776	0.2103	0.2569	0.8186	0.2203	0.2630	0.8376
Yilan	0.8166	1	0.8166	0.9266	1	0.9266	1	1	1
Hsinchu(cou)	0.3034	1	0.3034	0.3081	1	0.3081	0.3772	1	0.3772
Miaoli	0.4271	1	0.4271	0.5475	1	0.5475	0.3690	0.7603	0.4853
Nantou	0.3328	0.6045	0.5505	0.3454	0.6239	0.5536	0.3629	0.6010	0.6038
Yunlin	0.3465	1	0.3465	0.3478	1	0.3478	0.3578	1	0.3578
Chiayi(cou)	0.2712	0.3926	0.6908	0.2686	0.4073	0.6595	0.2694	0.4027	0.6690
Taitung	0.2587	0.3429	0.7544	0.2584	0.3132	0.8250	0.2591	0.3075	0.8426
Hualien	0.1802	0.1830	0.9847	0.2355	0.2658	0.8860	0.2099	0.2399	0.8749
Keelung	0.2241	0.2837	0.7899	0.2429	0.2990	0.8124	0.2917	0.3312	0.8807
Hsinchu(cit)	0.1998	0.2692	0.7422	0.1788	0.1790	0.9989	0.1756	0.1790	0.9810
Chiayi(cit)	0.1899	0.3268	0.5811	0.1198	0.1275	0.9396	0.1699	0.1867	0.9100
Av*	0.3714	0.6464	0.6358	0.3838	0.5748	0.7503	0.3894	0.5593	0.7554

Note: Av* Average, cou County, cit City, CCR overall efficiency, BCC technical efficiency, SCE scale efficiency.

Table 14. Stage 3 MPI analysis results (2015–2017) (source: compiled by the authors)

Administrative region	TFP	TC	EC
Kaohsiung	0.904	0.904	1
Taoyuan	1.038	1.067	0.973
Yilan	1.143	1.143	1
Hsinchu(cou)	1.021	1.031	0.990
Miaoli	0.882	0.882	1
Nantou	1.012	1.012	1
Yunlin	1.143	0.949	1.204
Chiayi(cou)	0.814	0.814	1
Taitung	0.975	0.975	1
Hualien	0.621	0.621	1
Keelung	0.913	0.903	1.011
Hsinchu(cit)	1.062	1.062	1
Chiayi(cit)	0.899	0.944	0.952
Av*	0.945	0.937	1.009

Note: Av* Average, cou County, cit City, TFP total factor productivity, TC technical change, EC technical change efficiency.

Nantou, and Hsinchu City, was caused by the growth of TC, while the EC of Taoyuan and Hsinchu County declined. The productivity growth of Yunlin was caused by the growth of EC, while TC was declining. Seven administrative regions, namely, Kaohsiung, Miaoli, Chiayi County, Taitung, Hualien, Keelung and Chiayi City, were rated as having productivity decline. In seven other administrative regions, the productivity decline of Kaohsiung, Miaoli, Chiayi County, Taitung, Hualien, and Keelung was caused by the decline of TC, while the EC of Keelung was growing. The productivity decline of Chiayi City was caused by the decline of both TC and EC. On the whole, the productivity decline of the DPR agencies in Taiwan was mainly due to the decline of TC, as in stage I.

As demonstrated by the stage III sensitivity analysis results shown in Table 15, the average number of licensed medical practitioners per 10.000 people (C1) had the greatest effect on the overall efficiency (if this indicator is ignored, the efficiency decreases from 0.3815 to 0.3414), followed by the average number of social welfare workers per 10.000 people (C2) and the average number of firefighters per 10.000 people (C3).

Table 15. Stage 3 sensitivity analysis results (source: compiled by the authors)

Year	All inputs	Ignored (C1)	Ignored (C2)	Ignored (C3)
2015	0.3714	0.3462	0.3393	0.3714
2016	0.3838	0.3363	0.3686	0.3838
2017	0.3894	0.3417	0.3581	0.3891
Av*	0.3815	0.3414	0.3553	0.3814
Influence order: C1 > C2 > C3				

Note: Av* Average, C1 the average number of licensed medical practitioners per 10.000 people, C2 the average number of social welfare workers per 10.000 people, C3 the average number of firefighters per 10.000 people.

Conclusions

In this study, the BSC served as the basic analytical framework for constructing a performance evaluation model for DPR agencies in Taiwan using collected indicator data. The efficiency and productivity of DPR agencies in the selected administrative regions in Taiwan were analyzed from each perspective of the BSC using DEA in conjunction with the MPI. The efficiency analysis showed that in each of the three years studied and each of the three stages, the DPR agencies were not efficient, suggesting that considerable improvements can be made. In stage I, the average number of people served by each government employee or teacher (L1) had the greatest effect on DPR efficiency. This reflects the current situation, wherein improvements in DPR services in Taiwan depend mainly on local government employees and teachers. In addition, the inefficiency in DPR indicates the current shortages in DPR-related personnel. In stage II, the supervision score of the Department of Medical Services (DMS) of the Ministry of Health and Welfare (I4) was the indicator that most significantly affected efficiency. This result suggests the importance of health and welfare-related personnel and resources to DPR services, and the relevant authorities should address the long-term shortages in such social welfare-related personnel and resources. In stage III, the input was a customer perspective indicator, and the output was a financial perspective indicator. However, because the public sector is nonprofit, the efficiency of each region in each year was relatively low. The average number of licensed medical practitioners per 10.000 people (C1) and the average number of social welfare workers per 10.000 people (C2) had the greatest effect on efficiency in stage III. This result not only corroborates the stage I analysis results but, more importantly, also highlights the current shortages in medical personnel and the potential problem that may arise when disasters occur in the future because of the lack of disaster relief personnel.

From the productivity analysis, the decline in the TFP in each stage was observed. For the individual administrative regions, the TC indicator exhibited the most significant growth. This result indicates that the managerial side of DPR in Taiwan currently requires improvement more than does the technical side. The analysis results showed that the current DPR system in Taiwan focuses on preparedness but lacks planning. In this study, we used DEA in conjunction with the MPI and the BSC as the analytical framework to construct a model for evaluating DPR performance and informing DPR services. The results of this study can be used by the relevant authorities for the DPR system in Taiwan to formulate long-term plans to improve the efficiency of the DPR system. More importantly, these results can also assist the central authorities in achieving the most effective allocation of DPR resources within a limited budget. However, the required indicator data were often missing or incomplete, resulting in deficiencies and limitations in the results. Thus, the central and local governmental DPR agencies must ensure that more DPR performance indicator data are measured and recorded.

Acknowledgements

The authors would like to thank the support from Ministry of Science and Technology (MOST), Taiwan (MOST 103-2119-M-309 -001 -).

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APPENDIXES

Table A1. Raw data of 13 administrative regions in 2015 (source: The National Statistics, R.O.C. (Taiwan); The Central Disaster Prevention and Response Council)

Administrative region	Financial			Customer			Internal/Business Process						Learning and Growth		
	F1	F2	F3	C1	C2	C3	I1	I2	I3	I4	I5	I6	L1	L2	L3
Kaohsiung	13,087.42	26,548.99	9,826.27	130.86	5.88	5.24	3	3	2	4	4	2	72.27	35524	3
Taoyuan	1,799.07	2,296.16	1,744.60	111.78	3.76	5.20	2	2	1	1	1	3	84.00	23427	2
Yilan	5,709.33	7,254.06	5,622.59	114.26	4.12	4.82	3	1	4	1	4	4	67.76	6265	1
Hsinchu(cou)	1,962.47	2,678.83	1,590.64	69.81	3.98	6.25	4	1	1	2	1	3	74.00	6824	2
Miaoli	3,184.63	2,750.49	1,984.18	77.32	3.35	6.49	1	2	1	3	4	1	70.15	7536	4
Nantou	2,243.85	2,572.87	2,148.60	85.98	4.18	6.98	1	3	2	1	1	1	65.04	7177	1
Yunlin	2,163.48	3,810.75	2,273.58	87.39	4.44	5.29	3	4	1	1	2	2	76.19	8523	3
Chiayi(cou)	2,580.48	3,077.41	1,857.84	95.14	4.74	7.13	1	1	4	4	3	1	67.71	7087	1
Taitung	2,607.50	1,896.58	1,461.58	100.77	8.02	12.61	2	4	1	4	2	1	42.76	4661	2
Hualien	2,065.66	2,005.20	1,798.13	147.99	5.97	7.23	2	1	1	1	1	1	56.71	5330	1.5
Keelung	2,336.67	2,134.88	1,656.23	104.24	6.35	6.09	4	2	1	3	1	2	72.37	4791	1
Hsinchu(cit)	2,005.12	2,068.05	1,353.51	128.64	4.51	5.19	1	1	2	2	1	3	77.11	5309	4
Chiayi(cit)	1,530.35	1,195.40	1,196.22	218.84	3.77	7.83	1	3	3	1	3	1	73.31	3423	3
Av*	3,328.93	4,637.67	2,654.92	113.31	4.85	6.64	2.15	2.15	1.85	2.15	2.15	1.92	69.18	9682.85	2.19

Note: Av* Average, cou County, cit City.

Table A2. Raw data of 13 administrative regions in 2016 (source: The National Statistics, R.O.C. (Taiwan); The Central Disaster Prevention and Response Council)

Administrative region	Financial			Customer			Internal/Business Process						Learning and Growth		
	F1	F2	F3	C1	C2	C3	I1	I2	I3	I4	I5	I6	L1	L2	L3
Kaohsiung	11,654.01	21,658.57	9,710.65	135.31	7.82	5.06	1	1	1	1	3	1	85.70	35282	4
Taoyuan	1,876.03	2,223.20	1,718.02	113.86	9.80	5.34	1	1	2	1	1	1	73.53	23612	1
Yilan	9,177.11	12,070.25	6,052.21	114.99	7.12	4.91	1	1	2	1	3	4	68.87	6213	2
Hsinchu(cou)	1,921.48	2,692.70	1,420.46	72.41	4.39	6.18	1	1	2	1	2	4	74.82	6871	2
Miaoli	3,141.48	2,404.19	1,908.91	79.27	3.85	6.51	1	3	1	2	1	1	71.60	7385	3
Nantou	2,176.32	2,634.56	2,187.07	88.23	6.71	6.52	2	1	1	1	1	1	65.65	7109	1
Yunlin	2,096.25	3,817.28	2,234.30	89.52	9.12	5.35	4	1	1	1	1	2	76.06	8554	4
Chiayi(cou)	2,050.11	3,142.32	1,853.42	96.16	19.66	7.08	1	1	1	3	4	1	67.58	7093	1
Taitung	2,330.04	1,825.93	1,423.03	104.70	12.86	11.78	2	4	4	4	2	2	43.62	4583	1
Hualien	2,179.59	1,989.32	1,740.29	152.43	6.21	7.05	1	1	1	1	1	1	57.95	5257	1
Keelung	2,227.96	2,169.40	1,654.65	106.48	6.42	6.26	3	1	1	2	1	1	74.29	4695	1
Hsinchu(cit)	2,080.28	2,135.05	1,344.87	135.05	10.28	5.28	1	3	3	3	1	3	78.58	5266	3
Chiayi(cit)	1,485.81	1,263.50	1,180.59	222.66	8.32	8.21	4	2	1	1	4	1	74.46	3393	4
Av*	3,415.11	4,617.41	2,648.34	116.24	8.66	6.58	1.77	1.62	1.62	1.69	1.92	1.77	70.21	9639.46	2.15

Note: Av* Average, cou County, cit City.

Table A3. Raw data of 13 administrative regions in 2017 (source: The National Statistics, R.O.C. (Taiwan); The Central Disaster Prevention and Response Council)

Administrative region	Financial			Customer			Internal/Business Process						Learning and Growth		
	F1	F2	F3	C1	C2	C3	I1	I2	I3	I4	I5	I6	L1	L2	L3
Kaohsiung	12,013.17	17,596.44	9,583.47	138.83	16.30	5.13	2	1	2	4	4	1	74.30	35175	1
Taoyuan	1,757.47	2,258.96	1,705.46	114.25	12.94	5.57	1	1	1	1	1	1	85.82	24140	1
Yilan	9,726.86	12,975.02	5,928.99	119.14	6.58	5.38	1	1	4	1	2	4	68.94	6240	1
Hsinchu(cou)	1,847.73	2,763.70	1,406.89	73.99	4.24	6.21	1	4	1	1	4	4	75.36	6924	2
Miaoli	2,246.98	1,988.66	1,777.33	81.37	6.97	6.89	1	1	4	1	2	1	71.67	7342	1
Nantou	2,209.34	2,631.67	2,127.07	90.90	9.34	6.95	1	1	1	1	1	1	66.20	7051	1
Yunlin	2,052.48	4,162.52	2,238.58	91.79	16.16	5.61	2	3	2	1	3	1	76.75	8474	3
Chiayi(cou)	2,051.72	3,187.13	1,843.85	99.14	19.50	7.61	1	2	1	2	1	1	67.73	7052	4
Taitung	2,435.96	1,795.71	1,436.37	108.79	12.64	12.18	3	2	3	2	3	2	43.42	4593	1
Hualien	2,254.74	1,845.98	1,719.68	157.14	9.88	7.56	1	1	1	1	1	1	57.87	5289	2
Keelung	2,378.32	2,274.30	1,626.21	107.71	6.64	6.10	1	1	1	4	1	1	75.31	4668	1
Hsinchu(cit)	1,896.86	2,205.10	1,308.42	137.15	10.29	5.49	2	4	2	3	1	3	79.44	5279	3
Chiayi(cit)	1,438.93	1,291.63	1,191.14	227.85	7.78	9.45	4	3	1	1	4	1	75.07	3374	4
Av*	3,408.50	4,382.83	2,607.19	119.08	10.71	6.93	1.62	1.92	1.85	1.77	2.15	1.69	70.61	9,661.62	1.92

Note: Av* Average, cou County, cit City.