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A Dynamic Performance Analysis of Productivity, R&D Capacity and Marketing Ability in the Information Service Industry

Chia-Chi Lee*
Department of Accounting Information, National Taipei University of Business

Shio-Ling Huang
Department of Accounting Information, National Taipei University of Business

Abstract

This paper uses data envelopment analysis (DEA) to perform a static operating efficiency evaluation and uses the Malmquist productivity index to measure cross-period changes in operating efficiency and productivity for information service firms. Two types of strategy matrices are built to identify those firms that are stable, progressing, or regressing in operating efficiencies. An assessment is made of those firms that focus on R&D or marketing. An empirical study is used to select 50 information service firms from the stock market in Taiwan. The Malmquist productivity index analysis shows that the average overall productivity, average overall efficiency change, and average overall production technique of the 50 firms are in progress. In addition, this paper develops two dynamic matrixes from the DEA perspective: the productivity matrix and the marketing ability and R&D capacity cross-analysis matrix. The productivity matrix aims at improving the firm's internal operating strategy. It may facilitate the development of a dynamic performance benchmarking reference for inefficient firms. The marketing ability and R&D capacity cross-analysis matrix aims at improving the firm's external marketing strategy. However, firms that are more oriented to marketing ability may, according to customer needs, make more appropriate customer segmentation and a establish product position that can help to improve operational efficiency and technological innovation. The combination of a productivity matrix and a marketing ability and R&D capacity cross-analysis matrix may help to create complete assessment and business strategy

* Corresponding author. Email: cclee.vera@msa.hinet.net
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guidelines for a firm's internal and external operation.

Keywords: Cross-period operating efficiency; Data envelopment analysis (DEA); Information service firms; Productivity matrix; Marketing ability and R&D capacity cross-analysis matrix

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資訊服務產業生產力、研發能力與行銷能力之動態績效分析

李家琪*
國立臺北商業大學會計資訊系

黃秀玲
國立臺北商業大學會計資訊系

摘要

本文以 50 家台灣資訊服務公司作為受評單位，使用資料包絡分析法執行資訊服務產業之靜態經營效率評估，以及使用麥氏生產力指數衡量經營效率與生產力之跨期變化；進一步發展兩個策略矩陣以辨識公司的經營效率是處於穩定、進步或退步狀態，以及評估公司是著重在研發或行銷層面的經營。麥氏生產力指數分析結果顯示，平均總生產力、平均總技術效率變動與平均整體生產技術變動皆處於進步的狀態。此外，本文發展兩個動態矩陣：生產力矩陣以及行銷與研發能力之交叉分析矩陣，生產力矩陣旨在改善公司的內部營運策略，其可協助無效率公司發展動態績效標竿的參考；行銷與研發能力之交叉分析矩陣旨在改善公司的外部行銷策略，然而，更傾向偏重行銷能力的公司可根據顧客需求，進行適當的顧客區分，並建立產品定位以有助於提高公司的經營效率與技術創新。生產力矩陣以及行銷與研發能力之交叉分析矩陣的結合，對於公司內部與外部的營運，可幫助其建立完整的績效評估與業務經營策略之方針。

關鍵詞：跨期經營效率、資料包絡分析法、資訊服務產業、生產力矩陣、行銷與研發能力之交叉分析矩陣

* 本文通訊作者。電子郵件信箱：cclee.vera@msa.hinet.net
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1. INTRODUCTION

According to statistical data from Taiwan's Directorate-General of Budget, Accounting and Statistics of the Executive Yuan (DGBAS), service industries include 13 categories: wholesale & retail industry, transport & warehousing industry, accommodation & food industry, information & communication industry, finance & insurance industry, real estate industry, professional, scientific and technological service industry, support service industry, public administration & national defense industry, educational service industry, healthcare & social work service industry, art, entertainment & leisure service industry, and other service industries. According to DGBAS statistics, the number of people engaging in service industries increased from 55.91% in 2001 to 58.84% in 2010, while the proportion of people engaging in service industries accounted for more than 50% of total employers. The information service industry exhibits the highest added value and is a knowledge-intensive industry that can be integrated with industrial professional knowledge and information communication technologies to assist other industries in improving operational efficiency and competitiveness (Lee & Huang 2015; Lee & Huang 2019).

In consideration of the above, the Executive Yuan included the information service industry as a focus among all service industries and classified it as a critical industry in stage 1 of its "Three Industries and Four Reforms" policy in order to assist industrial internationalization. As of 2010, the information and communication industry has also been one of the most rapidly growing service industries in the recent years. The top ten service industries in 2010 are also closely related with the information service industry, but according to statistics regarding output and productivity from DGBAS, the growth rate of the labor productivity index in the service industry has been slower than that of the manufacturing industry. In February 2010, OECD's Main Science and Technology Indicators Volume showed that the proportion of the R&D of the service industry to the total R&D of all enterprises in Taiwan is also lower than that of other countries (e.g. South Korea). The major predicaments facing Taiwan's service industry is its small market, which is detrimental to system development and brand establishment. In addition, the cost considerations limit the space of R&D and innovation.

The service scope provided by the information service industry is wide, including the hardware equipment required by enterprise informatization, the design of application software, system integration, portal operation, and website management (Lee & Huang 2015; Lee & Huang 2019). In recent years, the popularity of cloud services, social networks, and mobile devices, and development of the Internet of things have led to the increasing needs of information users, a rise in the demand for quantity of data, and a gradual increase in the provision of customized services. This trend also has caused information services to become an emerging industry that plays an important role during the process of national economic growth.

The information service industry is one of the 12 knowledge-based service industries under critical development in Taiwan. In this knowledge-intensive industry, employees have to continue expanding their professional knowledge and technologies. In addition, this industry attaches great importance to invisible assets concerning R&D and innovation. However, investments in visible assets within Taiwan's information service industry are rather few, and the outputs are mainly invisible products or services. Compared with other industries, the information service industry also has to constantly invest in R&D to create enterprise values (Lee & Huang 2015; Lee & Huang 2019). Moreover, due to the small domestic market, there is a need to aggressively expand into foreign markets to increase domestic firms' service opportunities. In terms of the industry's operating dimension, this paper investigates how to use information technologies to improve operating effectiveness and efficiency as well as how to employ marketing channels to expand products and services to various places around the world so as to capitalize on market niches.

Human resources are an important input factor in the information service industry (Lee & Huang 2015; Lee & Huang 2019). Improving employees' professional knowledge and technological ability and constant investment in R&D and innovation are the main sources for maintaining enterprise competitiveness. Although there are few firms in Taiwan's information service industry, operators have to constantly pursue product or service innovation to meet the needs of vast consumers and enterprises, grasp the latest trends, and engage in the interdisciplinary integration of resources. Information service firms must possess complete product service planning and marketing strategies to respond to future challenges and strengthen their own competitive advantages and niches in this ever-changing and competitive information environment.

In 1990, Taiwan's Institute for Information Industry divided the information service industry into six major segmented markets: package software, turnkey services, systems integration, professional services, processing services, and network services. In 2000, it integrated these six markets into three major categories: products, projects, and services. There are now numerous product and service categories in the information service industry, and firm managers cannot overlook the revenue performance and output of these various categories. Due to the diverse categories of products and services in the information service industry, employees of various different professional backgrounds and technologies are required to meet the needs of a wide range of consumers and provide complete service items and good quality. Therefore, this industry's features of diversified inputs and diversified outputs triggered the author's motivation to assess the operating performance of this emerging industry. This paper uses data envelopment analysis (DEA) as the tool for measuring the operational performance of the information service industry in order to provide suggestions on operational strategies for industry managers.

The literature has comprehensively applied DEA to performance assessment studies of various industries or fields, such as the banking industry (Krishnasamy et al. 2004; Lin & Mei 2006; Lin et al. 2007; Lin et al. 2009; Li 2009; Fethi & Pasiouras 2010; Juo et al. 2012), high-tech industry (Tan 2006; Chen & Chen 2009; Hadaya 2009; Seo et al. 2010), certified public accounting (CPA) industry (Lee 2009; Lee 2014), public sector (Simper & Weyman-Jones 2008; Söderberg 2009; Pestieau 2009; Herrala et al. 2012), diverse sectors (Boussemart et al. 2003; Odeck 2005; Daskovska et al. 2010; Halim 2010; Wadongo et al. 2010), teaching and learning effectiveness (Montoneri et al. 2011; Montoneri et al. 2012; Montoneri et al. 2013), and the information service industry (Lee & Huang 2015; Lee & Huang 2019), etc.

In this paper, the research database and subjects of Lee and Huang (2015, pp. 52-54) are applied to further derive new research topics. The purpose of this paper is to empirically analyze the static and dynamic operating efficiencies of selected cases and to identify those firms that offer a performance benchmark for inefficient firms from the perspective of the Charnes-Cooper-Rhodes (CCR) efficiency values and the Malmquist productivity index (MPI). It is emphasized that the definition of "dynamic performance benchmarking" in this paper means that the performance benchmark varies depending on the technical innovation and efficiency changes in a group of evaluated units.

There are three differences between this paper and previous studies. First, the evaluated units are classified into five groups according to the increase or decrease in the CCR efficiency values of the evaluated units for two consecutive years, so as to analyze whether the evaluated units remain stable and efficient, transit from inefficient to efficient, transit from efficient to inefficient, or record an improved efficiency or decreased efficiency during the two years. For example, identifying firms that have stable operations and that are progressing or are regressing may help to identify the core of their performance benchmarking collection. Second, technical and efficiency changes also constitute a productivity matrix, which can be used to conduct an operating strategy analysis and provide useful information in finding directions for improvement. This productivity matrix allows the construction of a clear goal for operation improvement and the clarification of firms' current strengths and weaknesses. In the same way, identifying firms that are oriented towards technology or operating efficiency may help in finding the strengths and weaknesses of those firms' operations and in coming up with solutions for their improvement. Third, this paper classifies all the evaluated information service firms according to their respective operating characteristics. For example, R&D capacity and marketing ability is used to develop the marketing ability and R&D capacity cross-analysis matrix. In addition, the performance analysis results of productivity matrix are integrated to examine the variation and suitability of a dynamic performance benchmarking reference collection and find out the most suitable learning objects. Identifying firms that have R&D capacity or marketing ability may provide the key factors positively affecting their business operations. This paper also creates a better overall marketing strategy as a reference for managers or business operators in the information service industry to develop their own business model and future business direction. Finally, this paper develops suitable operating and marketing strategies and establishes operating references for inefficient firms in the information service industry. The findings herein serve as a benchmark for firms to identify their core competencies, improve their operating efficiency, and strengthen their position in the global market. Differences between this paper and previous studies, as well as the research framework of Lee and Huang (2015), are also the innovation and contribution of this study.

2. OPERATING EFFICIENCY EVALUATION OF INFORMATION SERVICE INDUSTRY

Studies applying DEA on the performance assessment of the information service industry include Cheng and Dogan (2008), who develop an analytical framework to examine customer-centric marketing with Internet coupons and derive the conditions under which a firm should opt for changing the face value of Internet coupons. As a firm's information system improves in terms of having enhanced targeting accuracy at a lower cost, the changing face value of Internet coupons will become more prevalent. Debnath and Shankar (2008) discuss how mobile service providers in India create a loyal customer base by benchmarking their performances so as to retain existing customers and benefit from their loyalty. The results of benchmarking companies in terms of their efficiency are useful to telecom policy planners. The process allows planners to identify inefficient service providers that, by using efficient providers as their role models, could improve their own efficiency. Kwon et al. (2008) benchmark wireless mobile communication service providers in the U.S. through data such as annual reports showing assets, expenses, and revenues, and present that companies are relatively more efficient in asset management than in expense management. Merger activities adversely affect the efficiency of the companies in the models. Their conclusion is that companies require more effort to improve their efficiency after consolidation.

Lee and Huang (2015) perform a performance evaluation of information service firms in Taiwan, with results showing that more than half of the firms made progress both in pure technical efficiency and scale efficiency over the period 2009-2010. They suggest that these firms should continue to maintain their policies in R&D, product development, and operating scale. The business strategy of product or service specialization is more suitable for the information service industry. Lee and Huang (2019) aim at benchmarking the operations of inefficient firms in the information service industry. The findings show that, first, firms with a greater scale of business are relatively more efficient than those with a smaller scale of business in this industry. Second, the proportion of efficient firms in the TSE group (20%) is slightly higher than that in the OTC group (18.5%). Third, total non-operating revenues as the output should be improved the most while actual capital receipts as the input should be reduced the most, followed by the number of employees. Fourth, firms with a higher price-to-book ratio, higher proportion of major products, higher shareholding ratio of overseas subsidiaries, lower frequent chief officer changes, lower employees’ average seniority, and lower average age can reach optimal overall technical efficiency even though their scale of operations may be small. Different from other industries, firms in the information service industry have a higher proportion of younger employees who are creative and innovative.

3. METHODOLOGY

This paper applies the output-oriented Charnes-Cooper-Rhodes (CCR) model of DEA as the main assessment method to measure the yearly static operating efficiencies of the evaluated information service firms. Second, the cross-period changes in operating efficiency and productivity for information service firms are explored using MPI. Third, strategy matrices are constructed based on different segmentation criteria in order to develop suitable operating and marketing strategies for inefficient firms in the information service industry. Finally, this paper applies the independent sample t-test to identify group differences resulting from the segmentation criteria.

Farrell (1957) is the first to propose DEA by using a linear programming approach to identify the frontier curves of the evaluated units, which are named decision making units (DMUs). As a tool that measures the relative efficiency scores of a group of evaluated units, Charnes et al. (1978) and Banker et al. (1984) improve upon the concept of DEA. The DMUs on the frontier curves have efficiency scores equal to 1 and are considered to be efficient; those "inside" or "enveloped" by the frontier curves have efficiency scores inferior to 1 and are considered to be inefficient. The distance between the inefficient DMUs and the frontier curves is the improvement needed for firms to become efficient. In practical terms, the improvement direction given by DEA helps DMUs to become more competitive in the global market (for more detailed reviews of the methodology, see Seiford & Thrall 1990; Ali & Seiford 1993; Lovell 1993; Lovell 1994; Charnes et al. 1995; and Seiford 1996).

3.1 Charnes-Cooper-Rhodes (CCR) Model

Debreu (1951), Koopmans (1951), and Farrell (1957) first introduce modern measurements of economic efficiency, but in their cases the concept of efficiency measurement is restricted to a single output and multiple inputs. Charnes et al. (1978) design the so-called "Charnes-Cooper-Rhodes (CCR) model", which measures the relative efficiency of each DMU and estimates the efficiency frontier by the ratio of linear combinations of inputs to linear combinations of outputs. The efficiency score of the CCR model corresponds to the overall technical efficiency of an evaluated unit. If the efficiency score equals 1, then the evaluated unit is efficient (optimal performance) and has constant returns to scale (CRS); if the efficiency score is less than 1, then the evaluated unit requires improvement (Lee 2009; Lin et al. 2009; Montoneri et al. 2011; Montoneri et al. 2012; Montoneri et al. 2013; Lee & Huang 2015; Lee & Huang 2019).

Charnes et al. (1978, p. 430) propose a measure of any DMU's efficiency that can be obtained as the maximum of the ratio of weighted outputs to weighted inputs, subject to the condition that similar ratios for every DMU are less than or equal to unity. In a more precise form, it is:

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \tag{1}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1; \qquad j = 1, \dots, n,$$

$$u_r, v_i \geq 0; \qquad r = 1, \dots, s; \qquad i = 1, \dots, m.$$

where, y_{rj}, x_{ij} (all positive) are the known outputs and inputs of the j^{th} DMU, and $u_r, v_i \geq 0$ are the variable weights to be determined by the solution of this problem, e.g., by the data on all DMUs that are being used as a reference set. The efficiency of one member of reference set j=1,…, n DMUs is rated relative to the others. It is thus represented in the function for optimization, as well as in the constraints, and is further distinguished by assigning it the subscript ‘0’ in the function (but preserving its original subscript in the constraints). The indicated maximization then accords this DMU the most favorable weighting the constraints will allow (Charnes et al. 1978, p. 430). Details are shown in the original paper of Charnes et al. (1978).

This paper applies the CCR model of DEA, which has been widely used in the literature. Chung et al. (2008) apply the CCR model of DEA and window analysis to evaluate the long-term performance of a product family mix at a wafer factory in Taiwan. Wu (2009) designs a hybrid model using DEA, decision trees, and neural networks to assess supplier performance. Sun (2011) utilizes a CCR model and MPI to analyze the efficiency and productivity growth of six industries in Taiwan’s Hsinchu Industrial Science Park for the period 2000-2006.

3.2 Introduction to Malmquist Productivity Index (MPI), Efficiency Change, and Technical Change

The efficiency measurement method by Farrell (1957) is in the context of constant returns to scale (CRS). If the time factor is taken into consideration (that is, in a cross-period model), then production technology may change over time. Based on CRS, Caves et al. (1982) divide the changes in productivity into changes in technical efficiency (the “catch-up”) and technical changes (the “frontier-shift”) and introduce MPI. They use the production function to measure an individual DMU’s productivity change in different periods. In other words, MPI = frontier-shift × catch-up. Here, MPI >1 represents the productivity progress during period t compared with that during period t-1, and MPI <1 represents a decline in productivity. Frontier-shift >1 expresses progress in the DMU’s overall technology, while frontier-shift <1 expresses a decline in the DMU’s overall technology. Catch-up >1 signifies that a firm is closer to the efficient frontier in period t than in period t-1, while catch-up <1 signifies that the DMU is further away from the efficient frontier in period t than in period t-1. Färe and Grosskopf (1992) combine Farrell's theory (1957) with the use of MPI by Caves et al. (1982). Their input, which is based on the productivity change's MPI, has since become notably used to evaluate the productive performance of various countries (Färe et al. 1994) and sectors, such as financial institutions (Sturm & Williams 2004), Spain's commercial banking sector (Grifell-Tatjé & Lovell 1997), Iranian cement companies (Mohammadi & Ranaei 2011), Taiwan's forests (Kao 2010), and education (García-Aracil & Palomares-Montero 2008; Johnes & Yu 2008).

Färe and Grosskopf (1992) employ MPI to analyze efficiency changes over time. Here, (X_i^t, Y_i^t) and (X_i^{t+1}, Y_i^{t+1}) denote the input/output data for the i^{th} municipality over periods t and t+1, which allow MPI to be expressed as:

$$MPI_i(t,t+1) = \frac{\theta_i^{t+1}(X_i^{t+1},Y_i^{t+1})}{\theta_i^t(X_i^t,Y_i^t)}\sqrt{\frac{\theta_i^t(X_i^{t+1},Y_i^{t+1})}{\theta_i^{t+1}(X_i^{t+1},Y_i^{t+1})}\frac{\theta_i^t(X_i^t,Y_i^t)}{\theta_i^{t+1}(X_i^t,Y_i^t)}} \tag{2}$$

where, $\theta_i^{t'}(X_i^t, Y_i^t)$ is the (CRS) efficiency score obtained by benchmarking the municipality's data for period t against the sample data for period t'. MPI values higher than one indicate productivity improvements, whereas low values correspond to productivity decay. The first term in (2) indicates the efficiency change, whereas the square root term represents the technological change (i.e., the shift in the efficiency frontier between periods t and t+1). For details, please refer to the paper of Färe and Grosskopf (1992).

There are data on K inputs and M outputs for N municipalities. The i^{th} municipality is represented by the vectors X_i and Y_i, respectively. The $K \times N$ input matrix X and the $M \times N$ output matrix Y represent the data for all municipalities. The efficiency of the i^{th} municipality is measured by the ratio $\theta_i = u_i Y_i / v_i X_i$, where $u_i, v_i \geq 0$ are the weight vectors corresponding to the outputs and inputs of the i^{th} municipality.

4. EMPIRICAL IMPLEMENTATION

4.1 Research Data

The research data used in Lee and Huang (2015, pp. 52-54) are also applied in this paper, which uses the annual financial statements of 50 firms in the information service industry in Taiwan from 2009 to 2010 to conduct an assessment of static and cross-period efficiencies. The 50 firms, represented by D1, D2, D3, D4, etc., up to D50, include 11 firms listed on the Taiwan Stock Exchange (TSE), 31 over-the-counter firms (OTC), and eight firms in the emerging stock market (denoted as ROTC). The empirical financial data come from the firms' annual reports, the Taiwan Market Observation Post System (TMOPS), and the Taiwan Economic Journal Data Bank (TEJ).

According to the Market Observation Post System, there are a total of 50 top TSE-listed and OTC-listed firms in Taiwan as of May 2014. According to revenue figures in 2013, the total annual revenue of the top five firms is as high as NT$58.14 billion, accounting for 49% of the annual revenue for all TSE-listed and OTC-listed firms in this industry during the year. According to business tax statistics levied by the Fiscal Information Agency of the Ministry of Finance in May 2014, the growth rate of the output turnover for the information service industry is-4.13% in 2009 and 2.29% in 2010. The fluctuation in the growth of turnover within these two years is significant and reflects the trend of a significant increase.

The main products and services provided by Taiwan's information service industry include online games and game software, 3D digital content, 3D CAD/CAM, CAE professional applications, network services, Internet advertising and marketing, authorized news graphics services, news graphics libraries, system integration services, information transfers, system platforms, banking terminal systems, peripheral and system integration, computer system management software, consultancy and maintenance services, personal computers, automation equipment, educational software, magazines, and so on (Lee & Huang 2015; Lee & Huang 2019).

When utilizing DEA, it is preferable that firms with high homogeneity in business condition or operational characteristics or similar firms with the same inputs and outputs be taken into account during the selection of DMU. This allows for an objective assessment to be performed under a consistent basis. In this paper, the information service industry is selected according to the industry classification in the TEJ Data Bank at first; then, firms featuring such business items and attributes are identified and collected one by one according to the main products and services mentioned in the preceding paragraph. Such firms are regarded as the research subjects to ensure the homogeneity of the evaluated units and facilitate the execution of DEA. The 50 firms selected in this paper all conform to such principles, as they all provide similar products and services and share similar business characteristics.

In addition, when conducting the DEA, the number of DMUs should be greater than two times the sum of the input items and output items. Because this paper has four input items and four output items, there should be at least 16 DMUs ((four input items + four output items) × 2 = 16). There are 50 firms from the information service industry in this paper, which is greater than the threshold of 16. Therefore, the number of DMUs is sufficient and the sample size conforms to the principle of DEA.

4.2 Choice of Input and Output Items

In this paper, the four inputs and four outputs for the performance assessment of the information service industry applied in Lee and Huang (2015, pp. 52-54) are applied as the indicators for operating efficiency analysis in this study. The four inputs include marketing expenses, R&D expenses, total assets, and total number of employees, and the four outputs include net operating revenues, operating profits, current net income, and cash flow from operating activities. Lee and Huang (2015, p. 54) apply Pearson correlation coefficients to discuss the relevance between inputs and outputs. The results show that there is a significant positive correlation between the four inputs and four outputs, up to the 1% statistical significance level, indicating that there is a significant positive correlation between the four inputs and outputs, i.e., the higher the four inputs are, the better the performance of the four outputs will be. This result is in line with the principle of isotonicity in DEA. Hence, this paper refers to Lee and Huang (2015)'s study and takes into account the industrial characteristics of the information service industry. This paper also selects the same four inputs and four outputs of Lee and Huang's study (2015, pp. 52-54) to conduct the empirical research. Table 1 presents the definitions of the input and output items.

Table 1: Definitions of input and output items

Outputs /Inputs	Items[a]	Definitions	References support
I1	Marketing expenses	Refers to the necessary expenses to maintain a firm's operations. Higher investment in marketing facilitates the presentation of the firm's key products to customers; customers will better understand the firm's products and develop familiarity and a preference for the products.	Agarwal and Mehrotra (2009); Grewal et al. (2009); Xu et al. (2009); Halim (2010); Hoang and Alauddin (2012).

I2	R&D expenses	A firm's sustainable operation depends on ongoing R&D and innovative growth in products, production processes, and service quality. Thus, it can maintain customer loyalty. In addition, high R&D expenses can indirectly show whether the firm is the leader in the market. Therefore, it also refers to the necessary expenses to maintain the firm's operations.	Pakes and Griliches (1980); Brown and Svenson (1998); Drongelen et al. (2000); Lee and Park (2005); Hashimoto and Haneda (2008); Sharma and Thomas (2008); Guan and Chen (2012).
I3	Total assets	They include current assets, long-term investments, fixed assets, intangible assets, and other small assets. Regardless of what type of asset, they are all key elements in the operations; they bring economic benefits and allow for stable operations. A firm with sufficient assets can avoid financial difficulties.	Brooks (2006); Solís and Maudos (2008); Halkos and Tzeremes (2012).
I4	Total number of employees	Creative employees can directly bring innovative products and attract potential customers; hence, high quality manpower is one of the key points in the performance assessment of the information service industry.	Anderson et al. (2000); Lu et al. (2010); Chiou et al. (2012).
O1	Net operating revenues	It refers to the net gross revenue minus sales returns and discounts.	Pacheco et al. (2006); Alsharif et al. (2008); Barros and Dieke (2008); Hsieh and Lin (2010); Yang (2010).
O2	Operating profits	It refers to the net operating revenue minus operating costs and expenses.	Oum et al. (2006); Vaninsky (2006); Hashimoto and Haneda (2008); Halkos and Tzeremes (2012); Juo et al. (2012).

O3	Current net income	It is the balance of the operating profits plus the non-operating revenue minus the non-operating expenditures and the income tax.	Düzakın and Düzakın (2007); Chen et al. (2009); Sueyoshi and Goto (2010); Gómez-Limón et al. (2012).
O4	Cash flow from operating activities	Its is the current net income in the income statement, adjusted for certain items. It is calculated according to the cash basis rather than an accrual basis. Cash flow is usually the most effective and robust profitability indicator; it is also an immediate and measurable indicator of liquidity.	Tsai et al. (2006); Cummins and Xie (2008); Banker et al. (2010); Demirbag et al. (2010); Psillaki et al. (2010); Lee and Pai (2011).

Notes: [a] The units for all inputs and outputs are thousands of New Taiwan Dollars (NT$), except for I4, which is in persons. In addition, the definitions of all the inputs and outputs refer to Lee and Huang's (2015) study.

4.3 Empirical Results and Analysis

4.3.1 Analysis of the Overall Technical Efficiency

Table 2 lists the 50 evaluated information service firms and gives their overall technical efficiency in 2009 and 2010. These values are calculated by means of the CCR model. In 2009, 12 DMUs reach an overall technical efficiency (i.e. a CCR score) of 1; two DMUs, D7 (0.997) and D2 (0.936), have an efficiency value of between 0.9 and 1 and turn efficient in 2010. In 2010, 18 DMUs reach an overall technical efficiency of 1, and only one DMU, D28 (0.990), has an efficiency value between 0.9 and 1. The average overall technical efficiency of all DMUs is 0.651 in 2009 and 0.649 in 2010. The average efficiency of all inefficient DMUs is 0.528 in 2009 and 0.452 in 2010. Generally, even though the inefficient DMUs regress in 2010, compared to 2009, there are still six DMUs that become efficient in 2010.

This paper divides the DMUs into five groups according to the progression or regression of their efficiency over the period 2009-2010. Group 1 (12 DMUs) has a CCR score of 1 in both 2009 and 2010 and constantly manifests overall technical efficiency. Group 2 (six DMUs) has a CCR score lower than 1 in 2009, but is progressing and shows overall technical efficiency in 2010. Group 3 (one DMU) has a CCR score of 1 in 2009, but regresses and turns inefficient in 2010. Group 4 (13 DMUs) has a CCR score lower than 1 in 2009 and 2010, but shows progress in 2010. Group 5 (18 DMUs) has a CCR score lower than 1 in 2009 and in 2010, but regresses in 2010. The 12 DMUs in Group 1 maintain their overall technical efficiency in a stable state. These DMUs are D3, D9, D19, D21, D22, D34, D35, D37, D38, D46, D47 and D48. Among these 12, seven DMUs (D3, D9, D19, D21, D22, D35 and D47) have produced in primary products and services of more than 75% and concentrate their efforts on their main industry instead of diversifying their business. In 2009, D19 (35 times), D47 (33 times), and D48 (24 times) are the three DMUs most referred to as being efficient by the inefficient DMUs. In 2010, the DMUs most referred to as being efficient are D19 (31 times), D47 (29 times), and D48 (20 times), but their reference frequencies slightly drop. Group 2 and Group 4 exhibit progressive operational efficiency, while Group 3 and Group 5 exhibit regressive operational efficiency. There are 19 firms in these two states, respectively. Overall, 31 firms are in an inefficient state for two consecutive years, suggesting that most firms in the industry have to review their operational issues and whether resources are being efficiently used.

From Group 4, Table 2 reveals that almost all the efficient DMUs (indicated in bold font) appear in both 2009 and 2010. This phenomenon shows the stability of performance benchmarking for the DMUs in Group 4. In other words, the DMUs belonging to Group 4, which is also the group showing progress in operating performance, have consistent reference DMUs. As for Group 5, even though the DMUs regress in operating performance, their benchmarking reference DMUs (indicated in bold font) are generally maintained in a stable state over the period 2009-2010.

From the reference DMUs of Groups 4 and 5, and according to the results of two consecutive years (2009-2010), this paper finds that the performance benchmark referred to by the inefficient DMUs also reflects consistent combinations. This suggests that the benchmarking firms (efficient DMUs) assessed using DEA are stable and objective. Therefore, firms in Groups 4 and 5 should refer to the operational model and characteristics of the benchmarking firms to improve their own inefficiency.

Table 2: DMU efficiency scores and reference DMUs in 2009 and 2010

Group	Quadrant[a]	Unit name[b]	CCR score [c]		Rank		Reference times		Reference DMUs [d]	
			2009	2010	2009	2010	2009	2010	2009	2010
1 (Having stable operating efficiency)	2	D3	1.000	1.000	1	1	3	3	D3	D3
	2	D9	1.000	1.000	1	1	1	0	D9	D9
	2	D19	1.000	1.000	1	1	35	31	D19	D19
	1	D21	1.000	1.000	1	1	1	0	D21	D21
	2	D22	1.000	1.000	1	1	0	0	D22	D22

	1	D34	1.000	1.000	1	1	0	0	D34	D34
	1	D35	1.000	1.000	1	1	2	2	D35	D35
	1	D37	1.000	1.000	1	1	9	5	D37	D37
	1	D38	1.000	1.000	1	1	1	8	D38	D38
	1	D46	1.000	1.000	1	1	0	1	D46	D46
	1	D47	1.000	1.000	1	1	33	29	D47	D47
	2	D48	1.000	1.000	1	1	24	20	D48	D48
2 (Progressing in operating efficiency and reaching efficient state)	1	D7	0.997	1.000	14	1	0	3	D37, D47, D48	D7
	2	D2	0.936	1.000	15	1	0	0	D48	D2
	2	D30	0.874	1.000	16	1	0	0	D9, D19, D48	D30
	1	D6	0.845	1.000	18	1	0	0	D3, D19, D21	D6
	2	D39	0.526	1.000	31	1	0	0	D19, D37, D48, D49	D39
	1	D5	0.437	1.000	38	1	0	0	D19, D37, D47, D48	D5
3 (Regressing in operating efficiency and becoming inefficient)	3	D49	1.000	0.880	1	20	1	0	D49	D3, D37, D46
4 (Progressing in operating efficiency)	2	D28	0.700	0.990	20	19	0	0	D3, D19, D47, D48	D3, D19, D38, D48
	1	D50	0.567	0.573	28	23	0	0	D19, D47, D48	D19, D47, D48
	2	D17	0.537	0.566	30	24	0	0	D19, D38, D47	D19, D38, D47
	1	D18	0.499	0.530	32	29	0	0	D19, D47, D48	D19, D47, D48
	2	D41	0.499	0.537	33	28	0	0	D19, D47, D48	D19, D47, D48

	1	D44	0.493	0.617	34	21	0	0	D19, D37, D47, D48	D19, D37, D38, D47, D48
	1	D14	0.484	0.497	35	31	0	0	D19, D47	D19, D38, D47
	1	D11	0.396	0.542	40	25	0	0	D19, D47	D19, D38, D47
	2	D4	0.351	0.442	41	35	0	0	D19, D47, D48	D19, D47, D48
	2	D42	0.312	0.335	45	41	0	0	D3, D19, D37, D47, D48	D19, D37, D38, D47, D48
	1	D12	0.299	0.318	47	42	0	0	D19, D47	D19, D47
	1	D8	0.281	0.518	48	30	0	0	D19, D47	D19, D47
	1	D29	0.211	0.226	50	48	0	0	D19, D47, D48	D19, D47, D48
5 (Regressing in operating efficiency)	4	D32	0.849	0.451	17	34	0	0	D19, D47	D3, D19, D37, D38, D48
	4	D20	0.700	0.394	19	39	0	0	D19, D47	D19, D47, D48
	4	D23	0.699	0.591	21	22	0	0	D19, D47	D19, D47
	3	D33	0.668	0.477	22	33	0	0	D19, D47, D48	D19, D47, D48
	4	D36	0.619	0.225	23	49	0	0	D19, D47, D48	D19, D47, D48
	4	D31	0.600	0.540	24	27	0	0	D19, D47, D48	D19, D47, D48
	4	D24	0.572	0.480	25	32	0	0	D19, D47, D48	D19, D47, D48

	4	D45	0.570	0.541	26	26	0	0	D19, D47, D48	D19, D47, D48
	4	D16	0.568	0.442	27	36	0	0	D19, D47	D19, D47
	4	D13	0.563	0.395	29	38	0	0	D19, D47, D48	D19, D47, D48
	4	D15	0.482	0.435	36	37	0	0	D19, D47	D19, D47
	4	D40	0.448	0.183	37	50	0	0	D19, D37, D47, D48	D7, D19, D47, D48
	4	D27	0.414	0.348	39	40	0	0	D19, D47, D48	D19, D47, D48
	4	D43	0.345	0.312	42	43	0	0	D19, D37, D47, D48	D7, D19, D37, D47, D48
	4	D10	0.328	0.263	43	46	0	0	D19, D47, D48	D19, D38, D47
	4	D25	0.320	0.288	44	44	0	0	D19, D35, D37, D47	D19, D35, D47
	4	D26	0.300	0.269	46	45	0	0	D19, D35, D47	D19, D35, D47
	4	D1	0.263	0.263	49	47	0	0	D19, D37, D47, D48	D7, D19, D47, D48
Average of all DMUs			0.651	0.649						
Average of inefficient DMUs			0.528	0.452						

4.3.2 Analysis of the Malmquist Productivity Index (MPI)

Table 3 summarizes the changes in productivity of each DMU during the period 2009-2010. The average MPI is 1.053, which means that the average overall productivity of the 50 firms progresses over this time period. Of these, 28 DMUs, representing more than half of all DMUs, have MPIs higher than 1. This means that in 2010 their productivity shows progress as compared with 2009. Of note is that D5 and D8 have respective MPIs of 2.79 and 2.032. An analysis of D5's main products shows that 38.4% are in consultancy and maintenance services, 17.7% in workstations and servers, and 14.3% in storage equipment. Furthermore, D5's market share is 4.435% in 2009 and 4.456% in 2010. An analysis of D8's main products shows that 56.9% are in online game revenue, 42.2% in rental income, and 0.9% in license revenue, and that its market share is 0.262% in 2009 and 0.31% in 2010. D5 and D8 belong to Group 2 and Group 4, respectively, and both show progressive efficiency. This paper also observes that 22 DMUs have MPIs less than 1, which means that the productivity of 44% of the 50 DMUs regresses in 2010.

The average catch-up index is 1.035, denoting that the average change in the overall efficiency of the 50 firms is towards making progress. There are 19 DMUs with catch-up indices higher than 1; in other words, they are closer to the efficient frontier in 2010 than in 2009. They may have made some adjustments in operating management and business strategy to increase their efficiency. At 2.288, D5 makes the most progress in its catch-up index, showing that its progress in productivity is mainly due to more progress in its overall efficiency than that of the other DMUs. Of the other DMUs, 13 have catch-up indices equal to 1 and maintain their overall efficiency over the period 2009-2010. The other 18 DMUs, representing 36% of the 50 evaluated firms, have catch-up indices less than 1. It is thus recommended that these firms refer to the efficient DMUs as role models to make improvements in their management and decision making.

The average frontier-shift index is 1.026, which means that the average overall production technology of the 50 firms make progress over the period 2009-2010. Of these, 35 DMUs, representing 70%, have frontier-shift indices higher than 1, which means that their overall production technology progresses in 2010. This paper observes 15 DMUs with frontier-shift indices lower than 1, denoting that 30% of the 50 DMUs regress in overall production technology during the period 2009-2010. It is recommended that they improve their overall production technology, which is particularly important in a highly competitive industry like information services.

The overall average productivity index of the industry reflects a progression, of which 56% of firms exhibit progressive productivity. The progress of this industry is mainly caused by innovative R&D and improvements in technologies (70% of the firms). The change in operational efficiency for 38% of the firms reflects a progression, while 26% of them remain unchanged and 36% reflect a regression.

Table 3: Productivity changes for each firm during the period 2009-2010

DMU [a]	Quadrant [b]	MPI	Catch-up	Frontier-shift
D5	1	2.790	2.288	1.219
D8	1	2.032	1.840	1.105
D39	2	1.420	1.900	0.747
D11	1	1.410	1.368	1.031
D44	1	1.326	1.252	1.059
D6	1	1.301	1.183	1.100
D28	2	1.291	1.415	0.913
D38	1	1.289	1.000	1.289
D2	2	1.279	1.916	0.667
D4	2	1.245	1.262	0.987
D35	1	1.217	1.000	1.217
D34	1	1.186	1.000	1.186
D21	1	1.180	1.000	1.180
D7	1	1.150	1.003	1.147
D12	1	1.144	1.063	1.076
D37	1	1.139	1.000	1.139
D30	2	1.121	1.144	0.980
D46	1	1.116	1.000	1.116
D50	1	1.101	1.009	1.090
D29	1	1.100	1.071	1.028
D14	1	1.098	1.027	1.069
D47	1	1.090	1.000	1.090
D18	1	1.084	1.063	1.020
D41	2	1.075	1.077	0.998
D42	2	1.063	1.074	0.990
D1	4	1.053	1.000	1.053
D17	2	1.026	1.054	0.974
D26	4	1.015	0.896	1.133
D43	4	0.998	0.905	1.102
D25	4	0.989	0.900	1.099
D15	4	0.989	0.904	1.094
D45	4	0.977	0.948	1.030
D3	2	0.967	1.000	0.967

D48	2	0.964	1.000	0.964
D22	2	0.955	1.000	0.955
D23	4	0.943	0.846	1.115
D31	4	0.901	0.900	1.001
D24	4	0.894	0.841	1.064
D9	2	0.887	1.000	0.887
D16	4	0.883	0.778	1.136
D27	4	0.871	0.840	1.036
D10	4	0.846	0.802	1.055
D13	4	0.738	0.702	1.051
D33	3	0.700	0.715	0.979
D20	4	0.604	0.563	1.074
D49	3	0.583	0.880	0.662
D32	4	0.541	0.531	1.018
D40	4	0.442	0.408	1.081
D36	4	0.390	0.364	1.072
D19	2	0.240	1.000	0.240
Average		1.053	1.035	1.026
Number of DMUs > 1		28	19	35
Number of DMUs = 1		0	13	0
Number of DMUs < 1		22	18	15

4.3.3 Cross-analysis of the DMUs' Efficiency Progression/Regression and Productivity Matrix

As indicated in Table 3, this paper uses a management matrix to build a four-quadrant productivity and strategy matrix by comparing the overall production technology (i.e., the frontier-shift) and the efficiency change (i.e., the catch-up) over the period 2009-2010, as illustrated in Figure 1. Quadrant 1 includes DMUs that progress in both frontier-shift and catch-up or maintain values of 1 in each; quadrant 2 encompasses those that progress in catch-up but regress in frontier-shift; quadrant 3 comprises those that regress in both frontier-shift and catch-up; and quadrant 4 contains those that regress in catch-up but progress in frontier-shift.

According to the productivity features of different quadrants, Figure 1 offers suggestions for operating strategy. The results show that 70% of the DMUs belong in quadrants 1 and 4. This means that most of the DMUs have appropriate business strategies and show progress in overall production technology from a technological viewpoint. In addition, 31 DMUs belong to quadrants 1 and 2, which means that 62% of all DMUs have satisfactory operating efficiency. Two DMUs are located in quadrant 3, and they are advised to conduct a comprehensive review of their production technology and business strategy in order to meet the demands of the market and their clients, or merely to survive in the competitive IT service industry. For the information service industry, the productivity matrix reveals that most firms' development is technology-oriented. In this industry, if firms do not continuously upgrade their technology, develop products that are more suitable for customers, or provide customized services, they may soon lose their competitiveness. This paper confirms that the information service industry needs to pursue R&D technology and innovation, rather than only be concerned about business operations.

The definitions of the DMU groups in Section 4.3.1 allow the identification of whether the DMUs progress or regress in overall technical efficiency during the period 2009-2010. According to the definition, the DMUs in Group 1 are always efficient and maintain their efficiency of 1, the DMUs in Groups 2 and 4 show progression, and the DMUs in Groups 3 and 5 are regressing. Incorporating the analysis of MPI with the concept of the productivity matrix can help to more easily understand the reasons for changes in the DMUs' productivity and operating efficiency. Therefore, combining these two analysis techniques, as illustrated in Figure 1, may facilitate a more dynamic analysis and consequently the development of a dynamic benchmarking reference for inefficient DMUs.

The findings show seven DMUs (D21, D34, D35, D37, D38, D46 and D47) in Group 1 are located in quadrant 1, representing about 38.9% of all DMUs. Five DMUs (D3, D9, D19, D22 and D48) in Group 1 show regression in overall production technology (i.e. frontier-shift) and are located in quadrant 2. In Group 2, the DMUs progress in their CCR score. Three DMUs (D5, D6 and D7) are located in quadrant 1 and three DMUs (D2, D30 and D39) are located in quadrant 2. Similarly, in Group 3 there is only one DMU (D49) that regresses in its CCR score in 2010. It is located in quadrant 3. In Group 4, the DMUs progress in their CCR score. There are eight DMUs in quadrant 1 and five DMUs in quadrant 2. In Group 5, the DMUs regress in their CCR score. There is one DMU in quadrant 3 and there are 17 DMUs in quadrant 4. The above observation confirms that in quadrant 2 (where the DMUs show progress in overall efficiency) there are no DMUs belonging to Groups 3 and 5 (the groups that show regression in operating efficiency). Similarly, in quadrant 3 (where the DMUs show regression in operating efficiency and technology), no DMUs belong to Groups 1, 2, and 4 (the groups that are always efficient or show progress in operating efficiency). The results of Figure 1 and Table 2 are consistent and correspond to the findings.

Efficiency change (Catch Up)

Quadrant 2 (Oriented in operating efficiency) 1. Productivity features: DMUs regressing in overall production technology and progressing in overall efficiency. 2. Suggested strategy: continuing to maintain DMUs' operating strategy and trying to enhance R&D investment and production technology. A total of 13 DMUs in this quadrant: Group 1 (38.5%): D3, D9, D19, D22, D48 Group 2 (23.0%): D2, D30, D39 Group 3 (0%): - Group 4 (38.5%): D4, D17, D28, D41, D42 Group 5 (0%): -	**Quadrant 1 (Oriented in operating efficiency & technology)** 1. Productivity features: DMUs progressing both in overall production technology and overall efficiency. 2. Suggested strategy: continuing to maintain DMUs' R&D, production technology and operating strategy. A total of 18 DMUs in this quadrant: Group 1 (38.9%): D21, D34, D35, D37, D38, D46, D47 Group 2 (16.7%): D5, D6, D7 Group 3 (0%): - Group 4 (44.4%): D8, D11, D12, D14, D18, D29, D44, D50 Group 5 (0%): -
Quadrant 3 (Backward in operating efficiency & technology) 1. Productivity features: DMUs regressing both in overall production technology and overall efficiency. 2. Suggested strategy: adjusting DMUs' R&D and products policy to technology-oriented and trying to enhance operating efficiency by increasing technology investment and by merging or separating firms' business. A total of 2 DMUs in this quadrant: Group 1 (0%): - Group 2 (0%): - Group 3 (50%): D49 Group 4 (0%): - Group 5 (50%): D33	**Quadrant 4 (Oriented in technology)** 1. Productivity features: DMUs progressing in overall production technology and regressing in overall efficiency. 2. Suggested strategy: adjusting DMUs' operating strategy and continuing to maintain DMUs' R&D and production technology. A total of 17 DMUs in this quadrant: Group 1 (0%): - Group 2 (0%): - Group 3 (0%): - Group 4 (0%): - Group 5 (100%): D1, D10, D13, D15, D16, D20, D23, D24, D25, D26, D27, D31, D32, D36, D40, D43, D45

Overall production technology (Frontier

Figure 1: Productivity matrix

Figure 1 shows that the DMUs located in quadrants 1 and 2 mostly have stable operating efficiency (Group 1) or show progress in operating efficiency (Groups 2 and 4).

This means that DMUs which have better operating performance or that show continuing progress may increase their productivity (quadrant 1) or make progress in operating efficiency (quadrants 1 and 2). Two DMUs (D49 and D33) are located in quadrant 3, which means that DMUs which regress or that continue to regress in operating performance may experience a decrease in productivity and have a bottleneck with R&D technology and innovation. Therefore, these firms need to clarify whether their regression mainly comes from inefficiency in operating performance or from a lack of R&D technology and innovation. After this has been done, these firms must address their key weaknesses in order to enhance their business and productivity performance in the future. The DMUs located in quadrant 4 all regress in overall efficiency but make progress in overall production technology. The suggestion to these firms is to enhance their operating efficiency to move towards quadrant 1; moreover, their R&D technology and innovation experiences may be transferred to the DMUs located in quadrants 2 and 3, where they can become the learning role model.

4.3.4 Segmentation of DMUs by Firms' Marketing Ability or R&D Capacity

Research and development capacity plays an important role in information service firms' sustainable operation; however, it is sometimes a firm's marketing ability that determines whether the innovative products developed by the firm's R&D department are successful or not. Therefore, from the perspective of marketing strategy, this paper analyzes the influence of these two factors on firms' operating efficiencies. The first series of cases segment DMUs into high and low levels by I1's median in 2009, I1's median in 2010, or the median value of I1's average over the period 2009-2010, where I1 refers to the marketing ability in the market. The second series of cases implement a similar segmentation, but it is based on R&D capacity (denoted as I2). Each segmented level contains 25 DMUs.

Table 4 gives a comparison of the DMUs' various operating efficiencies and lists only the results of the DMUs segmented by the median value of the average of I1 or I2 over the period 2009-2010. This paper refers to the proposed productivity matrix illustrated in Figure 1 and also builds a four-quadrant marketing ability and R&D capacity matrix (denoted as the I1-I2 matrix) by comparing each DMU's average marketing ability (I1) and R&D capacity (I2) over the period 2009-2010, as illustrated in Figure 2. DMUs with an average of I1 and I2 that are both higher than the median values of the average of all the DMUs' I1 and I2 are located in quadrant 1; those that have a lower average I1 than the median value but a higher average I2 than the median value are located in quadrant 2;

those with an average I1 and I2 that are both lower than the median values are located in quadrant 3; those that have a higher average I1 than the median value but a lower average I2 than the median value are located in quadrant 4.

Table 4: Comparison of the DMUs' operating efficiencies based on the average marketing ability (I1) and the average R&D capacity (I2) over the period 2009-2010

Unit name [a]	Level of average I1 [b]	Level of average I2 [c]	Quadrant of I1-I2 matrix	Quadrant of productivity matrix	CCR 2009	CCR 2010	MPI	Catch-up	Frontier-shift
D5	High	High	1	1	0.437	1.000	2.790	2.288	1.219
D7	High	High	1	1	0.997	1.000	1.150	1.003	1.147
D8	High	High	1	1	0.281	0.518	2.032	1.840	1.105
D12	High	High	1	1	0.299	0.318	1.144	1.063	1.076
D47	High	High	1	1	1.000	1.000	1.090	1.000	1.090
D41	High	High	1	2	0.499	0.537	1.075	1.077	0.998
D1	High	High	1	4	0.263	0.263	1.053	1.000	1.053
D13	High	High	1	4	0.563	0.395	0.738	0.702	1.051
D15	High	High	1	4	0.482	0.435	0.989	0.904	1.094
D26	High	High	1	4	0.300	0.269	1.015	0.896	1.133
D43	High	High	1	4	0.345	0.312	0.998	0.905	1.102
D45	High	High	1	4	0.570	0.541	0.977	0.948	1.030
D18	Low	High	2	1	0.499	0.530	1.084	1.063	1.020
D29	Low	High	2	1	0.211	0.226	1.100	1.071	1.028
D2	Low	High	2	2	0.936	1.000	1.279	1.916	0.667
D4	Low	High	2	2	0.351	0.442	1.245	1.262	0.987
D9	Low	High	2	2	1.000	1.000	0.887	1.000	0.887
D30	Low	High	2	2	0.874	1.000	1.121	1.144	0.980
D48	Low	High	2	2	1.000	1.000	0.964	1.000	0.964
D33	Low	High	2	3	0.668	0.477	0.700	0.715	0.979
D16	Low	High	2	4	0.568	0.442	0.883	0.778	1.136
D23	Low	High	2	4	0.699	0.591	0.943	0.846	1.115
D31	Low	High	2	4	0.600	0.540	0.901	0.900	1.001
D36	Low	High	2	4	0.619	0.225	0.390	0.364	1.072
D40	Low	High	2	4	0.448	0.183	0.442	0.408	1.081
D14	Low	Low	3	1	0.484	0.497	1.098	1.027	1.069
D34	Low	Low	3	1	1.000	1.000	1.186	1.000	1.186
D50	Low	Low	3	1	0.567	0.573	1.101	1.009	1.090

D3	Low	Low	3	2	1.000	1.000	0.967	1.000	0.967
D19	Low	Low	3	2	1.000	1.000	0.240	1.000	0.240
D22	Low	Low	3	2	1.000	1.000	0.955	1.000	0.955
D28	Low	Low	3	2	0.700	0.990	1.291	1.415	0.913
D39	Low	Low	3	2	0.526	1.000	1.420	1.900	0.747
D24	Low	Low	3	4	0.572	0.480	0.894	0.841	1.064
D25	Low	Low	3	4	0.320	0.288	0.989	0.900	1.099
D27	Low	Low	3	4	0.414	0.348	0.871	0.840	1.036
D32	Low	Low	3	4	0.849	0.451	0.541	0.531	1.018
D6	High	Low	4	1	0.845	1.000	1.301	1.183	1.100
D11	High	Low	4	1	0.396	0.542	1.410	1.368	1.031
D21	High	Low	4	1	1.000	1.000	1.180	1.000	1.180
D35	High	Low	4	1	1.000	1.000	1.217	1.000	1.217
D37	High	Low	4	1	1.000	1.000	1.139	1.000	1.139
D38	High	Low	4	1	1.000	1.000	1.289	1.000	1.289
D44	High	Low	4	1	0.493	0.617	1.326	1.252	1.059
D46	High	Low	4	1	1.000	1.000	1.116	1.000	1.116
D17	High	Low	4	2	0.537	0.566	1.026	1.054	0.974
D42	High	Low	4	2	0.312	0.335	1.063	1.074	0.990
D49	High	Low	4	3	1.000	0.880	0.583	0.880	0.662
D10	High	Low	4	4	0.328	0.263	0.846	0.802	1.055
D20	High	Low	4	4	0.700	0.394	0.604	0.563	1.074
Average of quadrant 1 in I1-I2 matrix					0.503	0.549	1.254	1.135	1.092
Average of quadrant 2 in I1-I2 matrix					0.652	0.589	0.918	0.959	0.994
Average of quadrant 3 in I1-I2 matrix					0.703	0.719	0.963	1.039	0.949
Average of quadrant 4 in I1-I2 matrix					0.739	0.738	1.085	1.014	1.068

Notes: [a] DMUs are first in quadrant order of I1-I2 matrix, second in quadrant order of productivity matrix, then in ascending order of unit name. [b] It refers to the case of DMUs segmented by median of I1 average over 2009-2010. [c] It refers to the case of DMUs segmented by median of I2 average over 2009-2010.

The average values of the various efficiencies shown in Table 4 show that even though quadrant 1 of the marketing ability and R&D capacity matrix presents the lowest average CCR scores in 2009 and in 2010, it still has the highest average MPI, catch-up indicator, and frontier-shift indicator. This means that investing in marketing to develop a customer base and R&D technological innovation entail large time and cash requirements for any firm. It is difficult to receive current, satisfactory feedback of the obvious benefits in the period 2009-2010, where the static efficiencies show poor performance. However, from the aspect of changes in productivity trends over the two years, the overall changes in technical efficiency and the improvement in overall technology have progressed (these three indices are all greater than 1). It can also be seen from the trends over different periods that the relatively higher input resources in I1 and I2 can bring substantial benefits to firms in future years. This evidence confirms that the time-lag effect of these inputs can be reflected in future operating performance.

Figure 2 indicates five DMUs in quadrant 1 for the marketing ability and R&D capacity matrix, representing 41.7% of all 12 DMUs located in quadrant 1 of the productivity matrix. This means that the DMUs that make greater efforts both in marketing ability and R&D capacity have satisfactory feedback and good performance from the viewpoint of overall production technology and efficiency. In addition, six DMUs, representing 50.0% of the 12 DMUs, are located in quadrant 4 of the productivity matrix; that is, these firms are more oriented toward R&D technology and innovation. Overall, in quadrant 1 of the marketing ability and R&D capacity matrix, almost all the DMUs (11 of 12) emphasize investment in R&D technology and innovation.

The DMUs in quadrants 1 and 4 of the productivity matrix (see Figure 1) emphasize investment in R&D technology and innovation. Quadrant 1 in Figure 2 also shows higher efforts on marketing ability and R&D capacity. As compared with quadrants 1 and 4 (oriented in technology) shown in Figure 1, it is found in this paper that 91.7% of the 12 DMUs in quadrant 1 in Figure 2 are from quadrants 1 and 4 of the productivity matrix, and the nature of the two quadrants is also oriented in technology innovation. The results of Figures 1 and 2 are consistent, which is in line with the phenomenon in practice. Quadrant 1 of the marketing ability and R&D capacity matrix in Figure 2 shows that the greater the investments in R&D by information service firms, the higher their R&D capacity and the more advanced the overall production technology of the firms will be. In addition, it is also found from quadrant 4 of the marketing ability and R&D capacity matrix in Figure 2 that eight of the 13 DMUs are within quadrant 1 of the productivity matrix, accounting for 61.5%. This ratio is the highest among all the four quadrants of the productivity matrix, indicating that larger marketing investments by firms represent greater marketing efforts, which will enhance the contributions to improving operating efficiency, production technology, and innovation capability.

R&D capacity (I2)

Quadrant 2 (Making higher efforts on R&D capacity) 1. Operating features: DMUs belonging to low level in marketing ability but high level in R&D capacity. 2. Suggested strategy: continuing to maintain DMUs' R&D capacity operating strategy and trying to adjust marketing strategy, in order to enhance sales ability in market. A total of 13 DMUs in this quadrant and located in different quadrants of productivity matrix: In quadrant 1 (15.4%): D18, D29 In quadrant 2 (38.5%): D2, D4, D9, D30, D48 In quadrant 3 (7.6%): D33	**Quadrant 1 (Making higher efforts on marketing ability and R&D capacity)** 1. Operating features: DMUs belonging to high levels both in marketing ability and R&D capacity. 2. Suggested strategy: continuing to maintain DMUs' R&D capacity and marketing strategy. A total of 12 DMUs in this quadrant and located in different quadrants of productivity matrix: In quadrant 1 (41.7%): D5, D7, D8, D12, D47 In quadrant 2 (8.3%): D41 In quadrant 3 (0%): - In quadrant 4 (50.0%): D1, D13, D15, D26, D43, D45
Quadrant 3 (Making fewer efforts on marketing ability and R&D capacity) 1. Operating features: DMUs belonging to low levels both in marketing ability and R&D capacity. 2. Suggested strategy: adjusting both DMUs' marketing strategy and R&D policy, in order to quickly transmit customer needs to R&D department and to make appropriate products and services plans for different customer needs. A total of 12 DMUs in this quadrant and located in different quadrants of productivity matrix: In quadrant 1 (25.0%): D14, D34, D50 In quadrant 2 (41.7%): D3, D19, D22, D28, D39 In quadrant 3 (0%): - In quadrant 4 (33.3%): D24, D25, D27, D32	**Quadrant 4 (Making higher efforts on marketing ability)** 1. Operating features: DMUs belonging to high level in marketing ability but low level in R&D capacity. 2. Suggested strategy: focusing on in-depth understanding of customer demand, in order to segment different market needs, and to provide customized products and services. A total of 13 DMUs in this quadrant and located in different quadrants of productivity matrix: In quadrant 1 (61.5%): D6, D11, D21, D35, D37, D38, D44, D46 In quadrant 2 (15.4%): D17, D42 In quadrant 3 (7.7%): D49 In quadrant 4 (15.4%): D10, D20

Marketing ability (I1)

Figure 2: Marketing ability and R&D capacity cross-analysis matrix

This paper views the input status of I1 (marketing expenses) and I2 (R&D expenses) as a firm's ability in two areas: marketing development and R&D innovation. This paper divides firms into those with high marketing development ability and those with a low one according to their marketing development ability in order to investigate whether there are differences in operational efficiency, productivity index, and performance between two groups. Similarly, this paper also divides firms into those with high R&D innovation and those with low R&D innovation according to their R&D innovation ability so as to examine the difference in operational performance between these two groups. This paper employs the independent sample t-test, which is a univariate statistical method, to test whether there is any significant difference in the mean between these two groups of samples.

Tables 5 and 6 list the descriptive statistics and the independent sample t-tests of the operating efficiencies for the different high and low-level groups. In the case of the DMUs segmented by the median I1 in 2009, as shown in Tables 5 and 6, the independent sample t-test shows that MPI and the frontier-shift indicator reach statistically significant levels. The results of MPI and the frontier-shift indicator present that the high-level group is significantly higher than the low-level group, which means that firms focusing more on marketing have improved productivity and technological innovation and consequently have more operating or competitive advantages.

Table 5: Descriptive statistics of high and low-level operating efficiencies for different segmentations

Operating efficiencies / DMUs segmented by [a]	CCR 2009		CCR 2010		MPI		Catch-up		Frontier-shift	
level	High	Low	High	Low	High	Low	High	Low	High	Low
	Cases of DMUs segmentation based on I1									
I1's median in 2009	0.626	0.676	0.647	0.651	1.166	0.94	1.072	0.997	1.079	0.972
I1's median in 2010	0.650	0.652	0.619	0.679	1.026	1.079	0.955	1.114	1.074	0.978
Median of I1 average over 2009-2010	0.626	0.676	0.647	0.651	1.166	0.94	1.072	0.997	1.079	0.972
	Cases of DMUs segmentation based on I2									
I2's median in 2009	0.58	0.722	0.57	0.729	1.08	1.026	1.044	1.026	1.041	1.011
I2's median in 2010	0.58	0.722	0.57	0.729	1.08	1.026	1.044	1.026	1.041	1.011
Median of I2 average over 2009-2010	0.58	0.722	0.57	0.729	1.08	1.026	1.044	1.026	1.041	1.011

Table 6: Independent sample t-tests of different operating efficiencies for different segmentations

Operating efficiencies / DMUs segmented by [a]	CCR 2009			CCR 2010			MPI			Catch-up			Frontier-shift		
	t value	p value [b] (one-tailed)	Average deviation	t value	p value [b] (one-tailed)	Average deviation	t value	p value [b] (one-tailed)	Average deviation	t value	p value [b] (one-tailed)	Average deviation	t value	p value [b] (one-tailed)	Average deviation
	Cases of DMUs segmentation based on I1														
I1's median in 2009	-0.656	0.257	-0.05	-0.046	0.482	-0.004	2.149	0.018**	0.226	0.751	0.228	0.075	2.42	0.010***	0.107
I1's median in 2010	-0.03	0.488	-0.002	-0.703	0.243	-0.06	-0.48	0.317	-0.053	-1.623	0.057*	-0.159	2.147	0.018**	0.096
Median of I1 average over 2009-2010	-0.656	0.257	-0.05	-0.046	0.482	-0.004	2.149	0.018**	0.226	0.751	0.228	0.075	2.42	0.010***	0.107
	Cases of DMUs segmentation based on I2														
I2's median in 2009	-1.903	0.032**	-0.141	-1.924	0.030**	-0.159	0.486	0.315	0.053	0.181	0.429	0.018	0.637	0.264	0.03
I2's median in 2010	-1.903	0.032**	-0.141	-1.924	0.030**	-0.159	0.486	0.315	0.053	0.181	0.429	0.018	0.637	0.264	0.03
Median of I2 average over 2009-2010	-1.903	0.032**	-0.141	-1.924	0.030**	-0.159	0.486	0.315	0.053	0.181	0.429	0.018	0.637	0.264	0.03

In the case of the DMUs segmented by the median I1 in 2010, as shown in Tables 5 and 6, the catch-up and the frontier-shift indicators are statistically significant. The frontier-shift indicator of the high-level group is significantly higher than that of the low-level group, which means that firms targeting more on marketing development show obvious improvements in technological innovation. However, the catch-up indicator of the high-level group is not always higher than that of the low-level group.

In the case of the DMUs segmented by the median of the I1 average over the period 2009-2010, the results are the same as in the case of the DMUs segmented by the median I1 in 2009. This is because the composition of high and low-level DMUs of the average I1 are the same as those of I1 (in a slightly different order).

For the cases of DMUs segmented by the median I2 in 2009 and in 2010, and by the median of the I2 average over the period 2009-2010, the results of the descriptive statistics and the independent sample t-tests are identical for all cases, because the composition of high and low-level DMUs of the three cases is the same (in a slightly different order). The independent sample t-tests reveals that the CCR efficiency values in 2009 and 2010 of the high-level group are on average lower than those of the low-level DMUs. This means that firms focusing more on the development of R&D capacity have a lower current performance in static efficiency than firms which are less focused on the development of R&D capacity. For MPI and the catch-up and frontier-shift indicators, the values of the high-level group are on average higher than those of the low-level group, but they do not reach a statistically significant level. This means that there is no significant difference between these two groups; that is, R&D investment may have a minor impact, but it will not cause major changes in productivity for information service firms.

5. CONCLUSION

This paper uses the CCR model of DEA to evaluate static operating efficiency and utilizes MPI to measure cross-period changes in operating efficiency and productivity for information service firms. Based on changes in operating efficiency and different segmentation criteria, two strategy matrices are built in order to identify those firms that are stable, showing progress, or regressing in operating efficiency, as well as those that are orientated toward R&D technology and those that are marketing-oriented. The aim is to help develop suitable operating and marketing strategies for inefficient firms.

First, in respect of the analysis of static efficiency, using the reference set analysis of the five groups can help to better understand how the collection of performance benchmarking is suggested by DEA. The segmentation indicates that entrepreneurs and firms in the information service industry should be advised to retain the core of their performance benchmarking collection and gradually modify themselves after efficient firms in order to maintain the stability of their operating strategy. The MPI analysis finds that the average overall productivity, efficiency change, and production technology of the 50 firms show progress over the period 2009-2010. Of the 50 DMUs, 44% exhibit regression in productivity in 2010, while 36% make some adjustments in operating management and business strategy to increase their efficiency. The recommendation to 30% of the DMUs is that it is essential to improve their overall production technology due to the highly competitive nature of the information service industry.

Second, in respect of the analysis of dynamic efficiency, this paper also develops two dynamic matrices from the DEA perspective: the productivity matrix and the marketing ability and R&D capacity cross-analysis matrix. For the information service industry, the productivity matrix reveals that most firms' development is orientated towards technology. The information service industry pursues R&D technology and innovation rather than focusing on business operations. Incorporating MPI analysis into a management matrix may facilitate a dynamic analysis that leads to the development of a dynamic benchmarking reference for inefficient DMUs.

Third, the results from the marketing ability and R&D capacity cross-analysis matrix can provide information service providers with advice on how to focus on an in-depth understanding of the market demand for information products and services, make appropriate products and service plans to meet different customer needs, segment market needs, and provide customized services. Doing so can help firms develop products and services to meet customer needs and effectively enhance their firms' overall business performance.

Fourth, the information service industry changes rapidly and is highly competitive. R&D capacity and innovation are important driving factors in growth and progress, but the time-lags in the benefits mean that the R&D effect cannot be assessed by current performance. Conversely, customers' responses to products and services can be rapidly and immediately accessed through market surveys. Therefore, marketing is a key factor in business operations.

In conclusion, even though firms focusing more on marketing development have lower current performance in static efficiency than firms which are less focused on marketing development, they show an obvious improvement in productivity and technological innovation. Therefore, the development of marketing is essential to a firm's overall business. This paper also infers that firms targeting R&D technology innovation may see more costs in 2009, but the benefits of R&D innovation will not be reflected in the same year. However, the efficiency changes between 2009 and 2010 reveal that the three indicators related to MPI, catch-up, and frontier-shift show some progress. Despite not reaching a significant level, the effect of investment in R&D innovation may gradually appear during the next year and perhaps have a positive impact on the firms' operating performance in future years. Combining a productivity matrix and a marketing ability and R&D capacity cross-analysis matrix may offer a more complete assessment that can help formulate business strategy guidelines for a firm's internal and external operations. It is the research contribution of this paper.

An empirical analysis is implemented by applying the traditional DEA CCR model in this study, but there are numerous DEA models that can be used to estimate the efficiency score, such as the slack-based measure model (SBM model) and Super SBM model. It is impossible to order the performance of firms based on the traditional CCR model. However, the Super SBM model can be applied to further rank the evaluated units with an efficiency value of 1, which is different from the traditional DEA model. It is recommended that future studies conduct analysis by applying the SBM and Super SBM models and that efficient firms be further divided and ranked more specifically, to be set as models for inefficient firms in respect of performance. Moreover, in order to simplify the research issues and procedures, data from only two years are used in this paper, which is a limitation of this study. It is recommended that future studies use data from three to five years to obtain more complete performance assessment results.

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