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DEA Evaluation of Performance of E-Business Initiatives

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INTRODUCTION

The Internet has experienced a phenomenal growth in attracting people and commerce activities over the last decade—from a few thousand people in 1993 to 150+ million in 1999, and about one billion by 2004 (Bingi et al., 2000). This growth has attracted a variety of organizations initially to provide marketing information about their products and services and, customer support, and later to conduct business transactions with customers or business partners on the Web. These electronic business (EB) initiatives could be the implementation of intranet and/or extranet applications like B2C, B2B, Web-CRM, Web-marketing, and others, to take advantage of the Web-based economic model, which offers opportunities for internal efficiencies and external growth.

It has been recognized that the Internet economic model is more efficient at the transaction cost level and elimination of the middleman in the distribution channel, and also can have a big impact on the market efficiency. Web-enabling business processes are particularly attractive in the new economy, where product life cycles are short and efficient, while the market for products and services is global. Similarly, management of these companies expects a much better financial performance than their counterparts in the industry, which had not adopted these EB initiatives (Hoffman et. al., 1995; Wigand & Benjamin, 1995).

EB allows organizations to expand their business reach. One of the key benefits of the Web is access to and from global markets. The Web eliminates several geographical barriers for a corporation that wants to conduct global commerce. While traditional commerce relied on value-added networks (VANs) or private networks, which were expensive and provided limited connectivity (Pyle, 1996), the Web makes electronic commerce cheaper with extensive global connectivity. Corporations have been able to produce goods anywhere and deliver electronically or physically via couriers. This enables organizations the flexibility to expand into different product lines and markets quickly, with low investments. Secondly, 24x7 availability, better communication with customers, and sharing of the organizational knowledge base allows organizations to provide better customer service. This can translate to better customer retention rates as well as repeat orders. Finally, the rich interactive media and database technology of the Web allows for unconstrained awareness, visibility, and opportunity for an organization to promote its products and services. This enhances organizations' abilities to attract new customers, thereby increasing their overall markets and profitability. Despite the recent dot-com failures, EB has made tremendous inroads in traditional corporations. Forrester Research in its survey found 90% of the firms plan to conduct some e-commerce, business-to-consumer (B2C), or business-to-business (B2B), and predicts EB transactions to rise to about $6.9 trillion by 2004. As a result, the management has started to believe in the Internet because of its ability to attract and retain more customers, reduce sales and distribution overheads, and global access to markets with an expectation of an increase in sales revenues, higher profits, and better returns for the stockholders (Choi & Winston, 2000; Motiwalla & Khan, 2002; Steinfield & Whitten, 1999; White, 1999).

BACKGROUND

It is important that we use a comprehensive performance evaluation tool to examine whether these EB initiatives have a positive impact on the financial performance. Managers are often interested in evaluating how efficiently EB initiatives are with respect to multiple inputs and outputs. Single-measure gap analysis is often used as a fundamental method in performance evaluation and best practice identification. It is extremely difficult to show benchmarks where multiple measurements exist. It is rare that one single measure can suffice for the purpose of performance assessment. In our empirical study, there are multiple measures that characterize the performance of retail companies. This requires that the research tool used here have the flexibility to deal with changing production technology in the context of multiple performance measures. Data envelopment analysis (DEA) is originally developed to measure the relative efficiency of peer decision-making units (DMUs) in a multiple input-output setting. DEA has been proven to be an excellent methodology for performance evaluation and benchmarking (Zhu, 2003).

Based on Cooper, Seiford, and Zhu (2004), the specific reasons for using DEA are given as follows. First, DEA is a data-oriented approach for evaluating the performance of a set of peer DMUs, which convert multiple inputs into multiple outputs. In our case, the DMUs can be, for example, corporations that have launched EB activities. For each corporation, each year can be regarded as a DMU. Second, DEA is a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data, as is done in statistical regression, for example, one floats a piecewise linear surface to rest on top of the observations. Because of this approach, DEA proves particularly adept at uncovering relationships that remain hidden in other methodologies. Third, DEA does not require explicitly formulated assumptions of functional form as in linear and nonlinear regression models. This flexibility allows us to identify the multi-dimensional efficient frontier without the need for explicitly expressing the technology change and organizational knowledge.

In order to discriminate the performance among the efficient DMUs, a super-efficiency DEA model in which a DMU under evaluation is excluded from the reference set is developed. However, the super-efficiency model has been restricted to the case of constant returns to scale (CRS), because the non-CRS super-efficiency DEA model can be infeasible (Seiford & Zhu, 1998; 1999; Zhu, 1996).

It is difficult to precisely define infeasibility. As a result, one cannot rank the performance of a set of DMUs. In fact, an input-oriented super-efficiency DEA model measures the input super-efficiency when outputs are fixed at their current levels. Likewise, an output-oriented super-efficiency DEA model measures the output super-efficiency when inputs are fixed at their current levels. From the different uses of the super-efficiency concept, we see that super-efficiency can be interpreted as the degree of efficiency stability or input saving/output surplus achieved by an efficient DMU. If super-efficiency is used as an efficiency stability measure, then infeasibility means that an efficient DMU's efficiency classification is stable to any input changes, if an input-oriented super-efficiency DEA model is used (or any output changes, if an output-oriented super-efficiency DEA model is used). Therefore, we can use +¥ to represent the super-efficiency score (i.e., infeasibility means the highest super-efficiency).

Chen (2004) shows that (i) if an efficient DMU does not possess any input super-efficiency (input saving), it must possess output super-efficiency (output surplus), and (ii) if an efficient DMU does not possess any output super-efficiency, it must possess input super-efficiency. We thus can use both input-oriented and output-oriented super-efficiency DEA models to fully characterize the super-efficiency.

Based on the above derivations, Chen, et al. (2004) are able to rank the performance of a set of publicly held corporations in retail industry over the period 1997-2000. Specifically, the objective of this study is to determine whether the financial data support the beneficial claims made in the popular literature that EB has boosted the bottom-line.

MAIN TRUST

To present our DEA methodology, we assume that there are n DMUs to be evaluated. Each DMU consumes varying amounts of m different inputs to produce s different outputs. Specifically, DMU_j consumes amount x_{ij} of input i and produces amount y_{rj} of output r. We assume that $x_{ij} \geq 0$ and $y_{rj} \geq 0$ and further assume that each DMU has at least one positive input and one positive output value.

The input-output oriented super efficiency models whose frontier exhibits VRS can be expressed as Seiford and Zhu (1999) in Box 1, where x_{io} and y_{ro} are respectively the ith input and rth output for a DMU_o under evaluation.

Let γ_o represent the score for characterizing the super-efficiency in terms of input saving, we have

$$\gamma_o = \begin{cases} \theta_o^{VRS-\text{super}*} & \text{if the input - oriented super - efficiency model is feasible} \\ 1 & \text{if the input - oriented super - efficiency model is infeasible} \end{cases}$$

Note that $\gamma_o \geq 1$. If $\gamma_o > 1$, a specific efficient DMU_o has input super-efficiency. If $\gamma_o = 1$, DMU_o does not have input super-efficiency. Similarly, let τ_o represent the score for characterizing the output super-efficiency, we have

$$\tau_o = \begin{cases} \phi_o^{VRS-\text{super}*} & \text{if the output - oriented super - efficiency model is feasible} \\ 1 & \text{if the output - oriented super - efficiency model is infeasible} \end{cases}$$

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