DETERMINING THE EFFICIENCY-ORIENTED CRITICAL DRIVERS FOR E-MARKET USING DATA ENVELOPMENT ANALYSIS

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Abstract

This paper identifies the efficiency-oriented critical drivers for e-market using a two-stage approach. The efficiency of twenty-six e-markets is investigated first with respect to their respective overall efficiency, technical efficiency and scale efficiency, leading to the identification of the fully efficient e-markets and the underlying source of inefficiency in the existing e-markets. The efficiency-oriented critical drivers for e-market are then investigated using Tobit regression analysis based on the outcome of the analysis in the first stage, resulted in the identification of five critical efficiency-based drivers including head office location, coverage, revenue model, mechanism and language. The study shows that the source of inefficiency in the e-market is due to the scale of production. It further reveals that an e-market is more efficient if it (a) is US based, (b) focuses on offering the products or services internationally, (c) adopts a single type of revenue model, (d) focuses on an auction transaction mechanism and (e) provides a single language service. The findings of this study help existing e-markets improve their efficiency by focusing on the efficiency-based critical drivers and provide new players in e-market with guideline for developing efficient e-markets.

Key words: E-market, Efficiency study, Data envelopment analysis, Tobit regression analysis.

1 INTRODUCTION

Electronic market (e-market) is a virtual marketplace in which buyers and sellers are brought together for exchanging goods, services or information (Dou and Chou, 2002; Grieger, 2003). It is enabled and facilitated by the advance of information and communication technologies, especially web technologies since the middle of 1990s (Grieger, 2003). E-market has been increasingly popular due to its potential benefits to organizations including strengthened customer relationships, ease of reaching the targeted market, improved efficiency and reduced costs, and greater competitive advantage (Standing and Lin, 2007), and to individuals including improved flexibility for shopping, reduced transaction costs, and increased choices for more products and services (Gefen and Straub, 2004). Evidence of its popularity can not only be found in the rapid growth of e-market product and service offerings, but also in the wealth of literature resulting from the active research in this area (Grieger, 2003; Standing et al., 2010). A simple online search shows that there are over 90 million active e-markets in the world with the increase of around 77 thousand new e-markets everyday (Domain tools, 2010), targeting more than 1.9 billion people across different industries and geographical regions (Internet World Stats, 2010).

The great number of trading opportunities on the internet, however, does not guarantee the success of individual e-markets. The new millennium, in fact, has witnessed the fall and the rise of many "dot.com" companies (Sarkis and Sundarraj, 2002; Ravichandran et al., 2007). A large number of e-market, such as Chemdex and Adauction, went out of business, others including e-Steel and Covisint, changed their business model from e-market operators to technology service providers (Zhao et al., 2009). On the other hand, hundreds of e-market, such as World Wide Retail Exchange and SciQuest have successfully survived and thrived from the "dot.com" crash. As a consequence, both e-market operators and its participants are cautious on the performance of e-market. Those e-markets that have survived from the "dot.com" crash need regularly review their performance for developing specific strategies to capitalize on the changing environment. Those e-market participants also need to find e-markets with the best performance for conducting business with. This calls for effective approaches for evaluating the efficiency of individual e-markets (Standing et al., 2010; Ho, 2010).

Despite the increasing demand for effective tools in evaluating the performance of individual e-markets for both e-market operators and participants, there is still limited academic literature available with even fewer studies based on rigorously tested empirical data due to the short history of e-market and the availability of empirical data (Ho, 2010). Existing research on the e-market performance evaluation either focuses on proposing evaluation frameworks (Wen et al., 2003; Duan et al., 2010; Ho, 2010), or on testing existing theories using conceptualized instruments or interviews (Harison and Boonstra, 2009; Law et al., 2010). They are not satisfactory due to various shortcomings including (a) biased results that are heavily dependent on the perception of researchers and instrument respondents, (b) ignorance of the financial information of individual e-markets such as cost and revenue in the evaluation model, (c) failure in assessing the relative performance of individual e-markets, and (d) inadequacy in identifying the efficiency-oriented drivers.

There are several approaches available for evaluating the performance of individual organizations including ratio analysis (Rouse et al., 2002) and statistical analysis (Sueyoshi and Goto, 2009). They are, however, inadequate for characterizing the overall efficiency while considering the multiple inputs and outputs simultaneously (Wen et al., 2003). Data envelopment analysis (DEA) (Charnes et al., 1978), on the other hand, is proven to be reliable for appropriately assessing the efficiency of individual organizations due to its capability of effectively handling the multiple input and output simultaneously in a given situation (Emrouznejad et al., 2008; Cook and Seiford, 2009).

The usefulness of DEA in the study of the efficiency of e-market is demonstrated by a number of existing studies (Barua et al., 2004; Serrano-Cinca et al., 2005; Ho, 2010). Barua et al. (2004), for example, apply DEA for investigating the efficiency of internet based companies with respect to specific timeframes. Serrano-Cinca et al. (2005) employ DEA for assessing the efficiency of dot.com firms in 2003. Ho (2010) combines DEA with grey relation analysis for classifying the evaluation measurements for the efficiency analysis of internet-based companies in 2005. These studies shed light on the use of DEA for the evaluation of e-market efficiency. They, however, fail to (a) differentiate the types of internet-based companies, (b) use the latest empirical data in the evaluation model and (c) identify the efficiency oriented drivers for the continuous development of e-market.

This paper identifies the efficiency-oriented critical drivers for e-market using a two-stage approach. The efficiency of twenty-six e-markets is investigated first with respect to their respective overall efficiency, technical efficiency and scale efficiency, leading to the identification of the efficient e-markets and the underlying source of inefficiency in the existing e-markets. The efficiency-oriented critical drivers for e-market are then investigated using Tobit regression analysis based on the outcome of the analysis in the first stage, resulted in the identification of five critical efficiency-based drivers including head office location, coverage, revenue model, mechanism and language. The study shows that the source of inefficiency in the e-market is due to the scale of production. It further reveals that an e-market is more efficient if it (a) is US based, (b) focuses on offering the products or services internationally, (c) adopts a single type of revenue model, (d) focuses on an auction transaction mechanism and (e) provides a single language service. The findings of this study help existing e-markets improve their efficiency by focusing on the efficiency-based critical drivers and provide new players in e-market with guidelines for developing efficient e-markets.

In what follows, Section 2 presents the introduction of the DEA model for efficiency analysis. Section 3 describes the development of the efficiency evaluation model within the e-market context. Section 4 discusses the evaluation results of DEA model and the Tobit regression analysis, leading to the identification of the efficiency based critical drivers. The last section draws the conclusion.

2 DEA ANALYSIS FOR EFFICIENCY STUDY

DEA is a mathematical approach for measuring the relative efficiency of comparable business units, known as the decision making unit (DMU) with respect to a given set of outputs and inputs in a specific situation (Charnes et al., 1978). It is popular due to its distinct advantages including (a) the capacity of simultaneously handling multiple inputs and multiple outputs, (b) the ability to adapting to various scales for measuring inputs and outputs, (c) the lack of an explicitly specified mathematical function in the modelling process, and (d) the capacity of pinpointing the source of inefficiency for individual organizations (Cook and Seiford, 2009).

DEA assesses the relative efficiency of comparable DMUs as the ratio of the weighted outputs to the weighted inputs, where the model selects the weights for each DMU for presenting it in the most favourable way (Charnes et al., 1978). It allows a DMU to automatically choose the weights for maximizing its own efficiency score while other DMUs do not produce a relative efficiency greater than one using the same weights. The efficiency scores derived fall in the range from zero to one. DMUs are considered as efficient if their efficiency scores reach one.

Giving a set of n DMUs, the pth DMU $(p = 1, 2, \ldots, n)$ utilizes m inputs x_{ip}, $(i = 1, 2, \ldots, m)$ to produce s outputs y_{rp}, $(r = 1, 2, \ldots, s)$. u_r $(r = 1, 2, \ldots, s)$ and v_i $(i = 1, 2, \ldots, m)$ are the weights to be applied to the r^{th} output and i^{th} input respectively. The efficiency study problem is formulated for finding out the optimal values of u_r and v_i so that the relative efficiency score E_p for DMUp is maximized, subject to the constraints that efficiency scores for other DMUs are less than or equal to one using the same u_r and v_i. The efficiency score E_p for each DMU p is obtained by solving:

$$E_p = \max \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}} \tag{1}$$

Subject to: $$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad j = 1, 2, \ldots, n, \qquad u_r, v_i \geq 0$$

The DEA model above originally proposed by Charnes et al. (1978) is known as the CCR model. It has two assumptions namely the input-oriented assumption and the constant return-to-scale assumption. The input-oriented assumption states that DMUs strive to minimize the inputs under a certain amount of outputs. It is widely used in studying the performance of DMUs in the monopolist markets, where the outputs are controllable (Barros and Alves, 2003). The constant return-to-scale assumption stipulates that DMUs are operating at an optimal scale (Charnes et al., 1978; Cook and Seiford, 2009), whose output will change by the same proportion as the change of input.

The constant return-to-scale assumption, however, cannot be satisfied in most cases (Banker et al., 1984; Cook and Seiford, 2009). To tackle this limitation in evaluating the efficiency of individual DMUs, the CCR model is extended, resulting in the development of several extended DEA models from different perspectives. Among the extensions, the BCC model (Banker et al., 1984) is the most representative one which is capable of accommodating the variable return-to-scale assumption. It allows the efficiency of a DMU to vary according to the scale of production.

In the e-market efficiency evaluation, the input-oriented assumption mentioned above in the CCR model (1) does not hold due to the fact that the outputs are outside the control of e-market. On the contrary, e-market attempts to maximize the output within a fixed pool of inputs. This always happens in the competitive markets where DMUs aim to maximise their outputs subject to market demand (Barros and Alves, 2003). To accommodate this need, an output-oriented CCR model is presented as

$$E_p = \min \sum_{i=1}^{m} v_i x_{ip} \tag{2}$$

$$\textit{Subject to:} \quad \sum_{r=1}^{s} u_r y_{rp} = 1, \ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j = 1, 2, ..., n \qquad u_r, v_i \ge 0$$

The efficiency scores calculated in the CCR model (2) represent the overall efficiency of an e-market (Charnes et al., 1978). The overall efficiency can be further decomposed into technical efficiency and scale efficiency. The breakdown of overall efficiency provides insight into the main sources of inefficiencies in an e-market. The technical efficiency measures the effectiveness with which a given set of inputs is used to produce the outputs without the consideration of production scale (Banker et al., 1984). The scale efficiency determines if the scale of production of an e-market is optimal (Cook and Seiford, 2009). The technical efficiency of e-market can be calculated by the output-oriented BCC model formulated as:

$$E_p = \min \sum_{i=1}^{m} v_i x_{ip} + v_o \tag{3}$$

$$\textit{Subject to:} \quad \sum_{r=1}^{s} u_r y_{rp} = 1, \ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - v_o \le 0 \qquad j = 1, 2, ..., n \qquad u_r, v_i \ge 0$$

The overall efficiency (2) divided by the technical efficiency (3) is the scale efficiency (Banker et al., 1984). The p^{th} e-market is considered to be fully efficiency when its overall efficiency score achieves one. The comparison of the scale efficiency score and the technical efficiency score sheds light on the main source of inefficiency of a DMU (Cooper et al., 2007).

3 EFFICIENCY EVALUATION MODELS

3.1 Inputs and outputs

The success of applying DEA for assessing the efficiency of DMUs relies on the appropriate selection of inputs and outputs for formulating and developing specific performance evaluation models in a given situation (Cook and Seiford, 2009). A commonly accepted rationale for the selection is that the inputs and outputs selected must conform to the purpose of the evaluation (Barros and Alves, 2003) and there is a positive correlation between inputs and outputs (Kao, 2010).

E-market is a virtual marketplace that consumes labour and expenditures in order to achieve its objectives including obtaining revenue like the traditional markets and generating an impact on the Internet (Serrano-Cinca et al., 2005). The typical inputs for the evaluation of traditional markets are the labour resources, like the number of employees (Keh and Chu, 2003; Barros and Alves, 2003; Yu and Ramanathan, 2009) and the non-labour resources, like capital (Keh and Chu, 2003; Sellers-Rubio and Mas-Ruiz, 2006, Perrigot and Barros, 2008). E-market differentiates itself with the traditional market only in its web presence. It needs labour and non-labour resources as inputs in order to gain the outputs. Along the line with the evaluation of traditional markets, the number of employees and capital are selected as the inputs in the e-market evaluation model. Capital here refers to the total assets used in running an e-market including the current assets, fixed assets and intangible assets.

The selection of outputs must comply with the objectives of the DMUs under evaluation (Barros and Alves, 2003). The objectives of running an e-market are to (a) make profit and (b) generate an impact on the Internet for gaining the market share. The former objective is consistent with that of the traditional markets. As a consequence, the widely accepted financial measures including sales (Barros and Alves, 2003; Sellers-Rubio and Mas-Ruiz, 2006; Yu and Ramanathan, 2009) and profit (Sellers-Rubio and Mas-Ruiz, 2006; Perrigot and Barros, 2008) in the study of efficiency evaluation of traditional markets are considered in the e-market efficiency evaluation model. To select the appropriate outputs for measuring the impact of an e-market on the Internet, a comprehensive review of the performance measurement of websites is conducted. Several metrics exist for the performance evaluation of websites, such as the number of visitors, page hits, time spent and page depth (Phippen et al., 2004; Serrano-Cinca et al., 2005). Constrained by the availability of the empirical data, this study selects the average number of the monthly visitor of an e-market as one of the outputs for reflecting the market share of an e-market on the Internet. The rationale behind this decision is that (a) only visitors can become customers (Phippen et al., 2004) and (b) it reflects the customer loyalty and customer satisfaction on the e-market due to the reason that only the customers who are interested in or satisfied with the e-market would come back to visit the e-market.

Another indicator for reflecting the impact of an e-market on the Internet is the page rank. Page rank is a link analysis algorithm used by the Google search engine for measuring the relative importance of a website (PageRank, 2010). It assigns a number ranging from 0 to 10 to each website for reflecting the importance of a website by considering more than 500 million variables and 2 billion terms. The page rank is selected as an output in the e-market performance evaluation model due to the fact that it is a comprehensive objective measurement of the influence of a website on the Internet (Brin and Page, 1998; Serrano-Cinca et al., 2010). Table 1 presents a summary of inputs and outputs in the e-market efficiency evaluation model.

3.2 Data

The e-market to be included in this study for DEA analysis must conform to three criteria. First, the e-market should differentiate itself from other Internet-based companies such as any company website or search engine by generating the revenue through the online sales. Second, the financial information of the e-market in year 2009 should be available from www.sec.gov, finance.yahoo.com or money.msn.com. Third, the number of monthly visitors and the page rank should be available from trafficestimate.com and prchecker.com respectively. As a result, thirty-eight e-markets are selected out of the four-hundred-and-sixty-five dot-com companies whose financial information is available. Twelve e-markets do not have the information of monthly visitors, and thus excluded from the sample, resulted in the twenty-six e-markets with all the required inputs and outputs information available.

A rule of thumb for selecting an appropriate sample size for DEA analysis is to ensure that it is at least three times larger than the total number of inputs and outputs so that the efficient DMU can be effectively discriminated from the inefficient ones (Banker et al., 1989). The number of e-market selected are greater than the three times of the total number of inputs and outputs $26 > 3 \times (2 + 4) =$

18. The size of the samples is thus appropriate in providing the meaningful DEA analysis results. Table 1 presents the descriptive statistics of outputs and inputs for the twenty-six e-markets.

Variables	**Units**	**Minimum**	**Maximum**	**Mean**	**Std. deviation**
Outputs					
Sales	('000) Dollar	2,114	52,902,000	4,832,455	11,932,970
Profit	('000) Dollar	1,328	11,347,000	1,552,889	3,035,382
Page rank	Number	4	9	7	1
Visitors	Number	4,300	472,585,000	42,519,165	111,904,161
Inputs					
Employees	Number	12	94,300	8,329	19,267
Capital	('000) Dollar	961	65,730,000	5,717,120	14,399,321

Table 1. Descriptive statistics of outputs and inputs

To assess the relationship between the inputs and outputs before proceeding to DEA analysis, the Pearson's correlation test (Hair et al., 2010) is conducted in the twenty-six e-markets. The prerequisite condition of the DEA model is that outputs must have a positive correlation with inputs (Kao, 2010). Table 2 shows the result of the correlation test. All the outputs demonstrate positive and significant correlations with the inputs. They are therefore appropriate to be included in the e-market performance evaluation model.

Inputs	**Outputs**			
	Sales	Profit	Page rank	Visitors
Employees	0.966 ***	0.802 ***	0.460 ***	0.258 *
Capital	0.766 ***	0.951 ***	0.342 *	0.221 *

****p≤0.001, **p≤0.01, *p≤0.05.*

Table 2. Correlation coefficients between inputs and outputs

4 EMPIRICAL ANALYSIS

4.1 DEA analysis

Table 3 presents the efficiency scores of the e-markets based on the CCR model and the BCC model respectively. The CCR model measures the overall operations efficiency of an e-market, while the BCC model computes only the technical efficiency of an e-market. Twenty-six e-markets under evaluation are ranked from the most efficient to the least in Table 3. The average efficiency scores of the e-markets in terms of overall efficiency, technical efficiency and scale efficiency are 0.71, 0.94 and 0.76 respectively. This indicates that the e-markets only achieve 71% efficiency. They could have obtained 29% more outputs using the same amount of inputs. The higher value in the technical efficiency score than the scale efficiency score suggests that the main source of the inefficiency of these e-markets is due to the scale of production (Cooper et al., 2004). Inefficient e-markets need either increase or decrease their production scale in order to boost the overall efficiency.

Six e-markets including AMZN, FIND, INSW, OSTK, PCLN and TZOO are fully efficient. They are in an optimal status in utilizing their resources for producing outcomes. Seven e-markets namely TWX, EBAY, FLWS, DSCM, DELL, ALBCF and NTES are only technically efficient but lack of the scale efficiency. This means that they are inefficient compared to their peers due to the fact that they do not operate at their most productive scale. The return-to-scale result of these e-markets shows that they are all in the stage of a decreasing return-to-scale. This suggests that these e-markets are too large in size to take a full advantage of their scales. To increase their overall efficiency, they can decrease the production scale via the closure of some business sections or separating their activities into distinct sections. Two e-markets BIDZ and VITC are efficient in scale but technically inefficient. It indicates that BIDZ and VITC only need to improve the allocation of inputs and outputs within the current production scale for increasing their overall efficiency scores.

Other eleven e-markets are neither technically efficient nor efficient in scale. To improve their overall efficiency, they have to optimize the allocation of inputs and outputs as well as upgrade the production scale. The relatively higher values in the technical efficiency scores in these e-markets compared to their scale efficiency scores suggest that they should first focus on the improvement of the production scale for promoting the their scale efficiency before dealing with optimizing the allocation of inputs and outputs. The associated return-to-scale results further indicate that they are in the stage of an increasing return-to-scale. As a result, adequately combining the business sections or the product and service offerings may help to increase their scale efficiency (Barros and Alves, 2003).

Code	Web Address	CCR efficiency	BCC efficiency	Scale efficiency	Return-to-scale
AMZN	http://www.amazon.com	1.00	1.00	1.00	Constant
FIND	http://www.quickverse.com	1.00	1.00	1.00	Constant
INSW	http://www.insweb.com	1.00	1.00	1.00	Constant
OSTK	http://www.overstock.com	1.00	1.00	1.00	Constant
PCLN	http://www.priceline.com	1.00	1.00	1.00	Constant
TZOO	http://www.travelzoo.com	1.00	1.00	1.00	Constant
TWX	http://www.timewarner.com	0.97	1.00	0.97	Decreasing
EBAY	http://www.ebay.com	0.85	1.00	0.85	Decreasing
FLWS	http://www.1800flowers.com	0.82	1.00	0.82	Decreasing
DSCM	http://www.drugstore.com	0.75	1.00	0.75	Decreasing
DELL	http://www.dell.com	0.67	1.00	0.67	Decreasing
ALBCF	http://www.alibaba.com	0.56	1.00	0.56	Decreasing
NTES	http://corp.163.com	0.42	1.00	0.42	Decreasing
CYOU	http://www.changyou.com	0.45	0.95	0.48	Increasing
VCST	http://www.viewcast.com	0.81	0.93	0.87	Increasing
TREE	http://www.lendingtree.com	0.47	0.92	0.51	Increasing
WWWW	http://www.web.com	0.34	0.91	0.37	Increasing
CRM	http://www.salesforce.com	0.58	0.90	0.65	Increasing
BIDZ	http://www.bidz.com	0.90	0.90	1.00	Constant
ERTS	http://www.ea.com	0.57	0.88	0.65	Increasing
CTRP	http://www.ctrip.com	0.34	0.86	0.40	Increasing
STMP	http://www.stamps.com	0.66	0.85	0.77	Increasing
VITC	http://www.vitacost.com	0.85	0.85	1.00	Constant
DIET	http://www.ediets.com	0.56	0.84	0.67	Increasing
ACOM	http://www.ancestry.com	0.64	0.84	0.76	Increasing
CRMZ	http://www.crmz.com/	0.36	0.70	0.52	Increasing

Table 3. DEA efficiency scores for e-market, 2009

4.2 Tobit regression analysis

To further explore the efficiency-oriented critical drivers of e-market, the Tobit regression analysis (Tobin, 1958) is conducted. Tobit regression is a multivariate regression technique for estimating the linear relationships between the independent variables and the dependent variable when the dependent variable is either left or right censored (Hoff, 2007). It is often adopted in the consequent stage of the DEA for exploring the critical factors that contribute to the efficiency of a DMU because the efficiency scores calculated in DEA are truncated between zero and one. The choice of the Tobit regression over other regression techniques based on the ordinary least squares is due to the advantage of the Tobit regression in effectively handling the censored dependent variable by providing the unbiased and consistent parameter estimation (Simar and Wilson, 2000).

The appropriateness of using the Tobit regression in conjunction with DEA for exploring the efficiency-oriented drivers is exemplified by several studies. Scheraga (2004), for example, adopts the Tobit regression analysis for studying the efficiency drivers of the global airline industry. Wang and Huang (2006) use the Tobit regression analysis for quantifying the efficiency drivers of the R&D activities. Perrigot and Barros (2008) employ DEA and Tobit regression analysis for investigating the technical efficiency of French retailers. Yu and Ramanathan (2009) assess the operational efficiency and the efficiency drivers of retail firms in China using DEA and Tobit regression analysis.

The selection of the independent variables in Tobit regression analysis should follow two criteria. First, the independent variables selected are not the conventional inputs and outputs in the DEA model so that the efficiency scores calculated by DEA are not highly correlated with the independent variables in the Tobit regression (Yu and Ramanathan, 2009). Second, the independent variables should be non-managerial factors that indirectly affect the efficiency of DMUs (Perrigot and Barros, 2008). As a consequence, the experience of e-market and the characteristics of e-market are considered as critical in contributing to the variance of the efficiency score in e-market. The details of the independent variables for measuring these two factors are shown in Table 4.

Factor	Variable	Description	Measures	Literature
Experience of e-market	Head office location	The administrative centre for directing the operation of the e-market.	Dummy, 1 = US, 2 = China	Yu and Ramanathan, 2009
	Years	Years in operation of the e-market.	Number	Yu and Ramanathan, 2009; Assaf et al., 2010
Characteristics of e-market	Product type	The type of products or services the e-market offers.	Dummy, 1 = Single, 2 = Multiple	Rosenzweig et al., 2010
	Coverage	The target area of the business for the e-market in terms of location.	Dummy, 1 = Local, 2 = International	Fodor and Werthner, 2004; Yu and Ramanathan, 2009
	Ownership	The identities of the equity holders in the e-market.	Dummy, 1 = Biased, 2 = Unbiased	White et al., 2007; Rosenzweig et al., 2010
	Revenue model	The way that an e-market generates revenue.	Dummy, 1 = Single, 2 = Multiple	Brunn et al., 2002; Buyukozkan et al., 2004
	Mechanism	The transaction mechanism adopted by the e-market.	Dummy, 1 = Fixed price, 2 = Auction, 3 = Mixed	Wang et al., 2002; Stockdale and Standing, 2004
	Language	The language displayed in the e-market.	Dummy, 1 = Single, 2 = Multiple	Buyukozkan et al., 2004

Table 4. Details of the independent variables selected in the Tobit regression model

The experience of an e-market is considered as an efficiency driver. The more experience of an e-market leads to a greater capacity for conducting e-market activities in a more efficient way (Assaf et al., 2010). To reflect the experience of an e-market, the head office location and the years of operation of the e-market are selected as the key factors (Yu and Ramanathan, 2009; Assaf et al., 2010). The head office is the central of a business with the knowledge on personnel management, new product development, quality control and operations strategy (Yu and Ramanathan, 2009). A different location of the head office of an e-market represents the different expertise and experience in running the e-market, which in turn contributes to the different level of efficiency in the e-market. The years of operation in an e-market is also related to the efficiency of the e-market because the operation of an e-market might involve “learning by doing” (Assaf et al., 2010). The longer history of the e-market is associated with more proficient of the operation, thus greater efficiency.

The characteristics of an e-market affect the efficiency of e-market (White et al., 2007). They are usually measured by six factors including product type, coverage, ownership, revenue model, mechanism and language (Stockdale and Standing, 2004; Buyukozkan et al., 2004). Product type is employed for measuring the product and service offerings in an e-market. It measures if a specialised product or service offering is more preferable than the diverse offerings in an efficient e-market. Coverage is used for capturing the market coverage of an e-market. The e-market can easily expand its reach to the international market with the use of Internet. The ease of expansion of business for e-market, however, does not guarantee the more profitability and higher efficiency (Brunn et al., 2002) due to extra expenses such as the cost of hiring more staff in charge of the overseas markets as well as managerial issues involved. It is thus worthwhile in investigating the contribution of the coverage of e-market to the e-market efficiency.

Ownership is used for measuring the characteristics of individual e-market owners. A number of the efficiency studies for the traditional markets examine the relationship between business ownerships and the efficiency which show that public markets are less profitable and less efficient than private ones (Wei et al., 2002; Brunn et al., 2002). E-market can be classified into biased e-markets and unbiased e-markets (Dou and Chou, 2002). It is therefore interesting to investigate the contribution of the ownership to the efficiency of e-market. The revenue model is designed for measuring how the way that an e-market charges customer contributes to the efficiency of an e-market. Mechanism and language are used for evaluating whether different transaction mechanisms used by e-markets and extra functions provided such as different language services in the e-markets explain the variance in the e-market efficiency.

To formulate the Tobit regression model for identifying the critical efficiency-based drivers in e-market, the technical efficiency scores obtained from the BCC model are used as the dependent variable. Eight factors discussed above including head office location, years of operation, product type, service coverage, ownership, revenue model, mechanism and language are considered as independent variables. The Tobit regression model can be defined as follows:

$$\theta_p = \beta_0 + \sum_{i=1}^{8} \beta_i x_{ip} + \varepsilon_p, \qquad p = 1, 2, \ldots, 26 \tag{4}$$

Where θ_p is the technical efficiency score for the p^{th} e-market derived from Table 3. β_i $(i = 1, 2, \ldots, 8)$ represent the estimated coefficients between the efficiency drivers and the technical efficiency score. x_i $(i = 1, 2, \ldots, 8)$ are eight factors discussed above. ε represents the measurement error involved in the parameter estimation process. The results of the Tobit regression are shown in Table 5.

Variable	Coefficient (β)	T-value	p-value
Head office	0.232	2.14 *	0.032
Years	-0.008	-0.60	0.551
Product type	0.024	0.19	0.852
Coverage	-1.153	-10.97 ***	0.000
Ownership	-0.185	-1.52	0.129
Revenue model	0.260	2.70 **	0.007
Mechanism	1.184	6.56 *	0.038
Language	0.891	18.21 ***	0.000

****$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$.*

Table 5. Results of Tobit regression

Significant relationships are found between the e-market efficiency score and the head office location, coverage, revenue model, mechanism and language. This highlights the criticality of these five factors as the efficiency drivers of e-market. All five factors are represented by dummy variables. The positive or negative sign for the coefficient represents the comparison results between the dummy groups. It pinpoints the group that has greater contribution to e-market efficiency. For example, the significant and positive relationship between head office location and the efficiency of e-market indicates that US based e-markets are more efficient than China based ones. The significant and negative influence of the coverage on the e-market efficiency shows that e-market is more efficient if its products and services offerings are covered internationally. The significant and positive relationship between revenue model, mechanism and language and the efficiency of e-market reveals that e-market is more efficient when it adopts a single revenue model, an auction-based transaction mechanism, and a single language service for conducting the e-business.

The head office location is identified as a critical driver for the efficiency of e-market. The Tobit regression analysis result shows that US based e-markets are more efficient than China based ones. This is consistent with the DEA results in Table 3. The plausible reasons might be the existence of the poorer e-market infrastructure (Markus and Soh, 2001) and the inadequate management experience in China than US (Silwa, 2000). In particular, Markus and Soh (2001) indicate that China lacks a well functioning electronic payment system and escrow services for facilitating the transactions in the e-market. In addition, Chinese managers are relatively inexperienced in adopting modern business practices in managing the operations of e-market (Silwa, 2000). These factors would explain the more efficient operations of e-market in US than those in China.

The coverage of an e-market is another important efficiency driver. The positive contribution of the focus on offering service and products internationally in an e-market to the efficiency of the e-market is in line with the previous findings in the traditional markets (Perrigot and Barros, 2008; Assaf et al., 2010). The DEA results show that 71% e-markets with a focus on offering service and products internationally are technically efficient. A possible explanation is that the businesses or individuals hardly need to participate in the e-market if they could buy the products or obtain the service locally (Madanmohan, 2005). This limits the profitability of the e-market with a focus on the local area and thus decreases its performance. The e-market with international focus for service and products offering, on the other hand, is a more attractive and reasonable choice for businesses or individuals to join in.

The transaction mechanism, revenue model and language service are also the critical drivers for e-market. The contribution of these factors to the efficiency of an e-market is explored in the existing studies (Buyukozkan et al., 2004; Madanmohan, 2005). Buyukozkan et al. (2004), for example, identify the e-market characteristics as the e-market performance evaluation criteria and highlight the contribution of these characteristics to the performance of an e-market. Madanmohan (2005) suggests that different transaction mechanisms, revenue model and language services adopted by the e-market may affect its efficiency. In this study, the Tobit regression results specify the contribution of these three factors to the efficiency of e-market by suggesting that e-market is more efficient by focusing on an auction based transaction mechanism, a single revenue model, and a single language service.

5 CONCLUSION

This paper presents an empirical investigation on the critical drivers for the e-market efficiency via a two-stage approach. The efficiency of twenty-six e-markets is investigated using DEA in the first stage with respect to their respective overall efficiency, technical efficiency and scale efficiency. The results show that e-markets under evaluation only achieve 71% of efficiency. They could have produced 29% more outputs using the existing pool of inputs. Six e-markets are fully efficient. The main source of inefficiency is due to the scale of production. The existing inefficient e-markets are either too large or too small in size for making a full use of their scale. They can either decrease the production scale via the closure of some business sections or increase the production scale via combining their products and services offerings for improving their overall efficiency.

The efficiency-based critical drivers of e-market are explored in the second stage using Tobit regression analysis. Eight efficiency drivers are regressed on the technical efficiency scores calculated in the first stage, leading to the identification of five critical drivers including head office location, coverage, revenue model, mechanism and language. The results indicate that e-markets are deemed to be more efficient if (a) its head office is located in US, (b) its product and service offerings cover internationally, (c) it adopts a single revenue model, (d) it uses an auction method for the price mechanism, and (e) it only focus on providing the single language service.

The contribution of this study to the existing research is three folds. First, it provides a systematic approach in effectively investigating the inefficiency source and efficiency oriented drivers in e-market which have seldom been done before. Next, it differentiates the e-market from other internet based companies in the efficiency evaluation. Last, it provides the evaluation results based on the latest empirical data. The findings of this study shed light on the way for improving the efficiency of existing inefficient e-markets and provide e-market developers with guidelines for building up an efficient e-market.

The limitation of this study lies in the small sample size. Due to the availability of data, especially the financial information of the e-market, only twenty-six e-markets are studied. This greatly limits the generalization of the findings in this study. Future research in this area can extend this study based on a larger sample size. To explore the pattern of the e-market efficiency improvement over a certain period, a longitudinal analysis can be conducted.

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