EVALUATING THE OPERATING EFFICIENCY OF ELECTRONIC MARKET USING A HYBRID APPROACH

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Abstract

This paper aims to evaluate the operating efficiency of e-market for exploring the efficiency-oriented critical drivers on the development of e-market. A hybrid approach consisting of data envelopment analysis (DEA) and bootstrapped Tobit regression analysis is adopted. The efficiency of forty-three e-markets is investigated with respect to their respective overall efficiency, technical efficiency and scale efficiency, leading to the identification of the efficient e-market and the underlying source of inefficiency in the existing e-markets. The efficiency-oriented critical drivers for e-market are then investigated using bootstrapped Tobit regression analysis based on the outcome of the DEA analysis, resulted in the identification of four critical efficiency-based drivers including the head office location, the coverage, the mechanism, and the social media engagement. 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 headquartered in the United State, (b) focuses on offering the products or services internationally, (c) has a fixed-price transaction mechanism, and (d) engages more in social media. 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 their efficient e-markets.

Keywords: *E-market, Efficiency study, Data envelopment analysis, Bootstrapped 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 (Grieger 2003; Duan et al. 2012). It is enabled and facilitated by the advance of information and communication technologies, especially web technologies since the middle of 1990s (Standing et al. 2010). E-market has been becoming 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, and to individuals including improved flexibility for shopping, reduced transaction costs, and increased choices for more products and services (Stockdale and Standing 2004) . The 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 (Internet Retailer 2014), targeting more than 7.0 billion people across different industries and geographical regions (Internet World Stats 2014).

The increasing trading opportunities on the internet, however, do not guarantee the success of individual e-markets. The new millennium 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 models from e-market operators to technology service providers (Zhao et al. 2009). In such a situation, both e-market operators and its participants are cautious on the performance of e-market. The survived e-markets need regularly review their performance for developing specific strategies to capitalize on the changing environment. The e-market participants need to find e-markets with the best performance for their business. This calls for effective approaches for evaluating the efficiency of individual e-markets (Standing et al. 2010; Cao and Yang 2011).

Despite the increasing demand for effective tools in evaluating the performance of individual e-markets, there is little research available due to the relatively 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). Such studies are unsatisfactory due to various shortcomings including (a) biased results that are heavily dependent on specific situations, (b) ignorance of the financial information of individual e-markets, (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, 2010; Ho 2010; Cao and Yang 2011). 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 the grey relation analysis for classifying the evaluation measurements for the efficiency analysis of internet-based companies in 2005. Cao and Yang (2011) adopt a two-stage DEA model for investigating the causes of inefficiency of dot.com firms with the use of the dataset from Serrano-Cinca et al. (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 aims to evaluate the operating efficiency of e-market for exploring the efficiency-oriented critical drivers. A hybrid approach consisting of DEA and bootstrapped Tobit regression analysis is adopted. The efficiency of forty-three e-markets is investigated 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 bootstrapped Tobit regression analysis based on the outcome of the DEA analysis, resulted in the identification of four critical efficiency-based drivers including the head office location, the coverage, the mechanism and the social media engagement. 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 headquartered in the United States, (b) focuses on offering products or services internationally, (c) has a fixed-price transaction mechanism, and (d) engages more in social media. 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 describes the development of an efficiency evaluation model within the e-market context. Section 3 discusses the evaluation results of DEA model and the bootstrapped Tobit regression analysis, leading to the identification of the efficeincy based critical drivers. The last section draws the conclusion.

2 THE MODEL

This study applies a hybrid approach to evaluate the operating efficiency of e-market for determining the efficiency based critical drivers. A number of DEA models are used first to measure the efficiency of the relevant e-markets. This is followed by a bootstrapped Tobit regression model for exploring the critical drivers for the e-market efficiency.

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 $(p = 1, 2, ..., n)$ utilizes m inputs x_{ip}, $(i = 1, 2, ..., m)$ to produce s outputs y_{rp}, $(r = 1, 2, ..., s)$. u_r $(r = 1, 2, ..., s)$ and v_i $(i = 1, 2, ..., m)$ 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:

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

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

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 outputs will change by the same proportion as the change of inputs.

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

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

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

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 the overall efficiency provides insights 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:

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

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

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).

The success of applying DEA for assessing the efficiency of DMUs relies on the appropriate selection of inputs and outputs for formulating 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 profits 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. 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. 2010). 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 because only the satisfied or interested customers would come back to visit the e-market.

Another indicator for reflecting the impact of an e-market is the page rank. Page rank is used by the Google search engine for measuring the relative importance of a website (PageRank 2014). 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 because it is a comprehensive objective measurement of the influence of a website (Serrano-Cinca et al. 2010).

To further explore the efficiency-oriented critical drivers of e-market, a bootstrapped Tobit regression analysis is conducted. Tobit regression (Tobin 1958) 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 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 is due to the advantage of the Tobit regression in effectively handling the censored dependent variable by providing the consistent parameter estimation (Hoff 2007).

The efficiency scores obtained in the DEA analysis are correlated with the explanatory variables in the Tobit regression analysis. This means that the Tobit regression estimates are biased (Simar and Wilson 2007). To overcome this problem, a bootstrap procedure proposed by Simar and Wilson (2007) is conducted in the Tobit regression analysis in this study.

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 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, seven variables are considered as the potential efficiency drivers for e-markets. Table 1 shows the details of the independent variables and their measures.

The head office location is measure by a dummy variable. 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. 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. 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.

Variable	Description	Measures	Literature
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
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	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
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
Social media engagement	The number of posts in social media.	Number	Internet Retailer 2014; Qu et al. 2013

Table 1. Details of the independent variables selected in the Tobit regression model

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. Mechanism is used for evaluating whether different transaction mechanisms used by e-markets explain the variance in the e-market efficiency. Social media engagement is measured by the number of posts that e-market have in four main social media, including Facebook, Pinterest, Twitter, and Youtube (Internet Retailer 2014).

To formulate the Tobit regression model for exploring the critical efficiency-based drivers in e-market, the technical efficiency scores obtained from the BCC model are used as the dependent variable. Seven factors discussed above are considered as independent variables. The Tobit regression model can be defined as follows:

$$\theta_p = \beta_0 + \sum_{i=1}^{7} \beta_i x_{ip} + \varepsilon_p, \qquad p = 1, 2, \ldots, 43 \tag{4}$$

Where θ_p is the technical efficiency score for the p^{th} e-market derived from Table 3. β_i $(i = 1, 2, \ldots, 7)$ represents the estimated coefficients between the efficiency drivers and the technical efficiency score. x_i $(i = 1, 2, \ldots, 7)$ are the seven factors discussed above. ε represents the measurement error in the parameter estimation process.

3 ANALYSIS AND DISCUSSION

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 2014 should be available from www.sec.gov or finance.yahoo.com. Third, the number of monthly visitors and the page rank should be available from trafficestimate.com and prchecker.com respectively. As a result, fifty-seven e-markets are selected out of the six-hundred-and-eighty-five dot-com companies whose financial information is available. Fourteen e-markets do not have the information of monthly visitors, and thus excluded from the sample, resulted in the forty-three 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 $43 > 3 \times (2 + 4) = 18$. The size of the samples is thus appropriate in providing the meaningful DEA analysis results. Table 2 presents the descriptive statistics of outputs and inputs for forty-three e-markets.

Variables	**Units**	**Minimum**	**Maximum**	**Mean**	**Std. deviation**
Outputs					
Sales	('000) Dollar	11,063	61,093,000	6,813,588	14,562,258
Profit	('000) Dollar	75	12,186,000	635,287	2,339,761
Page rank	Number	3	8	6	1
Visitors	('000) Number	66	480,571	33,349	78,812
Inputs					
Employees	Number	40	165,000	15,201	31,879
Capital	('000) Dollar	5,180	47,540,000	5,406,370	10,699,102

Table 2. Descriptive statistics of outputs and inputs

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. Forty-three 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 0.61, 0.92 and 0.66 respectively. This indicates that the e-markets only achieve 61% efficiency. They could have obtained 39% 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.

Nine e-markets including PCCC, NFLX, OSTK, NILE, FGNT, GKNT, VCST, TREE, and SALE are fully efficient. They are in an optimal status in utilizing their resources for producing outcomes. Fifteen e-markets namely STMP, TZOO, ACOM, CDW, WWWW, CHGG, EBAY, SYX, EA, PRTS, AMZN, BBY, DELL, HSNI, and PRSS are only technically efficient but lack of the scale efficiency. They are inefficient compared to their peers because 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. One e-market BIDZ is efficient in scale but technically inefficient. It indicates that BIDZ only need to improve the allocation of inputs and outputs within the current production scale for increasing its overall efficiency scores.

DMU	Name	CCR efficiency	BCC efficiency	Scale efficiency	Return-to-scale
PCCC	PC Connection Inc.	1.00	1.00	1.00	Constant
NFLX	Netflix Inc.	1.00	1.00	1.00	Constant
OSTK	Overstock.com Inc.	1.00	1.00	1.00	Constant
NILE	Blue Nile Inc.	1.00	1.00	1.00	Constant
FGNT	FragranceNet.com Inc.	1.00	1.00	1.00	Constant
GKNT	ThinkGeek Inc.	1.00	1.00	1.00	Constant
VCST	ViewCast.com Inc.	1.00	1.00	1.00	Constant
TREE	Tree.Com, Inc.	1.00	1.00	1.00	Constant
SALE	RetailMeNot Inc	1.00	1.00	1.00	Constant
STMP	Stamps.com Inc.	0.97	1.00	0.97	Decreasing
TZOO	Travelzoo Inc.	0.96	1.00	0.96	Decreasing
ACOM	Ancestry.com Inc.	0.89	1.00	0.89	Decreasing
CDW	CDW Corp.	0.87	1.00	0.87	Decreasing
WWWW	Web.com Group, Inc.	0.74	1.00	0.74	Decreasing
CHGG	Chegg Inc.	0.71	1.00	0.71	Decreasing
EBAY	eBay Inc.	0.71	1.00	0.71	Decreasing
SYX	Systemax Inc.	0.70	1.00	0.70	Decreasing
EA	Electronic Arts Inc.	0.65	1.00	0.65	Decreasing
PRTS	U.S. Auto Parts Network.	0.55	1.00	0.55	Decreasing
AMZN	Amazon.com Inc.	0.54	1.00	0.54	Decreasing
BBY	Best Buy Co.	0.51	1.00	0.51	Decreasing
DELL	Dell Inc.	0.49	1.00	0.49	Decreasing
HSNI	HSN Inc.	0.49	1.00	0.49	Decreasing
PRSS	CafePress.com	0.38	1.00	0.38	Decreasing
CTRP	Ctrip.com International Ltd.	0.11	0.99	0.12	Increasing
GRPN	Groupon Inc.	0.22	0.99	0.22	Increasing
NTES	NetEase, Inc.	0.35	0.99	0.35	Increasing
SPLS	Staples Inc.	0.44	0.92	0.47	Increasing
COA	Coastal Contacts Inc.	0.45	0.92	0.48	Increasing
VPRT	Vistaprint NV	0.34	0.89	0.38	Increasing
FLWS	1-800-Flowers.com Inc.	0.48	0.89	0.53	Decreasing
VITC	Vitacost.com, Inc.	0.56	0.88	0.63	Decreasing
ZU	Zulily Inc.	0.42	0.88	0.48	Decreasing
SFLY	Shutterfly Inc.	0.42	0.86	0.49	Decreasing
KSS	Kohl's Corp.	0.44	0.84	0.53	Decreasing
AVP	Avon Products Inc.	0.28	0.83	0.34	Decreasing
VITC	Vitacost.com Inc.	0.55	0.77	0.71	Decreasing
BIDZ	Bidz.com Inc.	0.75	0.75	1.00	Constant
MSM	MSC Industrial Supply Inc.	0.33	0.71	0.46	Increasing
CAB	Cabela's Inc	0.27	0.70	0.38	Increasing
LINTA	Liberty Interactive Corp.	0.27	0.68	0.39	Increasing
WTW	Weight Watchers Inc.	0.24	0.57	0.43	Increasing
CRMZ	Creditriskmonitor Inc.	0.31	0.49	0.62	Increasing

Table 3. DEA efficiency scores for e-market, 2014

There are eighteen e-markets which 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 the allocation of inputs and outputs. The associated return-to-scale results further indicate that eleven e-markets including CTRP, GRPN, NTES, SPLS, COA, VPRT, MSM, CAB, LINTA, WTW, and CRMZ 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).

To further investigate the drivers for the e-market efficiency, the bootstrapped Tobit regression is conducted using Stata version 12.0. Table 4 shows the results. The regression model fits the data well with χ^2 67.25 (*p=0.000*). Significant relationships are found between the e-market efficiency score and the head office location, coverage, mechanism and social media engagement. This highlights the criticality of these four factors as the efficiency drivers of e-market.

Variable	Observed coefficient	Bootstrap std. error	*t*-value
Head office	0.357	0.136	2.62*
Years	-0.047	0.033	-1.42
Product type	0.205	0.233	0.88
Coverage	-0.044	0.005	-8.53**
Ownership	-0.132	0.121	-1.09
Mechanism	0.882	0.154	5.70**
Social media engagement	0.224	0.065	3.46*

*Note: ***p≤0.001, **p≤0.01, *p≤0.05. C = 500 samples with size 43.*

Table 4. Results of bootstrapped Tobit regression

Head office location, coverage and mechanism 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 headquartered e-markets are more efficient than China headquartered ones. This is consistent with the results in Table 3 which shows all the efficient e-markets are headquartered in US. This may be due to the existence of the poorer e-market infrastructure (Markus and Soh 2001) and the inadequate management experience in China (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).

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. This finding is in line with the previous efficiency studies conducted in traditional markets (Perrigot and Barros 2008; Assaf et al. 2010). The DEA results show that 67% e-markets with a focus on offering service and products internationally are technically efficient. A possible explanation is that 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 e-market with a focus on the local area, thus decreasing its performance. The e-market with an international focus for service and products offering is a more attractive choice for businesses or individuals to join in.

The significant and positive relationship between mechanism and the efficiency of e-market reveals that e-market is more efficient when it adopts a fixed-price transaction mechanism. 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 and revenue model adopted by the e-market may affect its efficiency. In this study, the Tobit regression results specify the contribution of these two factors to the efficiency of e-market by suggesting that e-market is more efficient by focusing on a fixed-price based transaction mechanism. This is because the fixed-price based mechanism tends to generate more profit than the auction based mechanism (Einav et al. 2013), thus leading to the increase of efficiency in e-market. The significant and positive relationship between social media engagement and the efficiency of e-market shows that e-market is more efficient if it constantly post in four main social media sites including Facebook, Pinterest, Twitter, and Youtube. This finding is consistent with studies that examine the relationship between online social activities and business performance (Constantinides et al. 2009; Qu et al. 2013). Constantinides et al. (2009), for example, suggest that the use of social media as one of the advertising channel will increase the competitive advantage of the business. Qu et al. (2013) find that hyperlinks to social media on the e-tailers' storefront are beneficial to e-tailers because they reveal e-tailers' alliance networks in online marketplaces.

4 CONCLUSION

This paper presents an empirical investigation on the efficiency of e-markets for exploring the critical drivers for the e-market efficiency using a hybrid approach. The efficiency of forty-three e-markets is investigated using DEA with respect to their respective overall efficiency, technical efficiency and scale efficiency. The results show that e-markets under evaluation only achieve 61% of efficiency. The 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 or increase the production scale for improving their overall efficiency.

The efficiency-based drivers of e-market are explored using bootstrapped Tobit regression analysis. Seven efficiency drivers are regressed on the technical efficiency scores calculated in the first stage, leading to the identification of four critical drivers including head office location, coverage, mechanism and social media engagement. The results indicate that e-markets are deemed to be more efficient if it (a) is headquartered in the United State, (b) focuses on offering the products or services internationally, (c) has a fixed-price transaction mechanism and (d) engages more in social media.

The contribution of this study is three folds. First, it provides a systematic approach in effectively investigating the inefficiency source and efficiency 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 forty-three 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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