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Enterprise risk management: a DEA VaR approach in vendor selection

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Enterprise risk management (ERM) has become an important topic in today's more complex, interrelated global business environment, replete with threats from natural, political, economic, and technical sources. The development and current status of ERM is presented, with a demonstration of how risk modelling can be applied in supply chain management. Within supply chain management, a major managerial decision is vendor selection. We start with discussion of the advanced ERM technology, i.e. value-at-risk (VaR) and develop DEA VaR model as a new tool to conduct risk management in enterprises. A vendor selection set of data is used to demonstrate how this model can be used to assess supply risks in ERM. Such models provide means to quantitatively improve decision making with respect to risk.

Keywords: enterprise risk management; supply chains; vendor selection; data envelopment analysis (DEA); value-at-risk (VaR)

1. Introduction

The concept of enterprise risk management (ERM) developed in the mid-1990s in industry, expressing a managerial focus. ERM is a systematic, integrated approach to managing all the risks facing an organisation (Dickinson 2001). It has probably been encouraged by traumatic recent events such as 9/11 and business scandals, including Enron and WorldCom (Walker *et al.* 2003, Baranoff 2004). A recent Tillinghast-Towers Perrin survey (Miccolis 2003) reported that nearly half of the insurance industry used an ERM process (with another 40% planning to do so), and 40% had a chief risk officer. But consideration of risk has always been part of business, manifesting itself in mediaeval coffee houses such as Lloyd's of London, spreading risk related to cargos on the high seas. Businesses exist to cope with specific risks efficiently. Uncertainty creates opportunities for businesses to make profit. A very profitable trend is to outsource production. Outsourcing offers many benefits, but also has a high level of inherent risk (Beasley *et al.* 2004). ERM seeks to provide the means to recognise and mitigate risks. The field of insurance developed to cover a wide variety of risks, related to external and internal risks, covering natural catastrophes, accidents, human error, and even fraud. Financial risk has been controlled through hedge funds and other tools over the years, often by investment banks. With time,

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it was realised that many risks could be prevented, or their impact reduced, through loss-prevention and control systems, leading to a broader view of risk management.

Contingency management has been widely systematised in the military, although individual leaders have practised various forms for centuries. Systematic organisational planning recently has been observed to include scenario analysis, giving executives a means of understanding what might go wrong, giving them some opportunity to prepare reaction plans. A complicating factor is that organisation leadership is rarely a unified whole, but rather consists of a variety of stakeholders with potentially differing objectives.

Enterprise risks are inherently part of corporate strategy (Dickinson 2001). Thus consideration of risks in strategy selection can be one way to control them. Dickinson thus views ERM as top-down by necessity. For example, currency risk arises because a company chose to involve itself in international activity. Divestment (and incorporation) often arises from desires to obtain legal protection as a means to reduce risk. An example was the formation of Alyeska Pipeline Service Company in 1970 to build and service the Alaska pipeline. Outsourcing is a more recent trend, usually adopted to gain lower production costs, but also used to reduce core organisational risk. Because risk is an inherent part of strategy, Dickinson suggested that it needs to be measured in terms of organisational objectives.

Moskowitz *et al.* (2000) presented a vendor selection scenario involving nine vendors with stochastic measures given over 12 criteria. This model was used by Wu and Olson (2008) in comparing DEA with multiple criteria analysis. In this paper, we start with a discussion of the advanced ERM technology, i.e. value-at-risk (VaR) and develop DEA VaR model as a new tool to conduct risk management in enterprises. We use Moskowitz *et al.* (2000) data to demonstrate utilising our approach in ERM.

While risk needs to be managed, taking risks is fundamental in any business. Profit by necessity requires accepting some risk (Alquier and Tignol 2006). ERM provides tools to rationally manage these risks. Monte Carlo simulation has been one of the most popular approaches for quantitative ERM in the past. This paper also compares the proposed DEA VaR model with simulation in a supply chain vendor selection problem. Thus we not only present a new quantitative ERM model, but also use simulation to demonstrate ERM tools reported in the literature. This demonstration provides how quantitative models are implemented in a good ERM case, i.e. supply chain outsourcing risk. Section 2 of the paper discusses ERM definitions and its status. Section 3 develops our approach. Section 4 addresses supply chain vendor selection used, with results. Section 5 provides conclusions.

2. What is ERM?

Enterprise risk can include a variety of factors with potential impact on any organisation's activities, processes, and resources. External factors can result from economic change, financial market developments, and dangers arising in political, legal, technological, and demographic environments. Most of these are beyond the control of a given organisation, although organisations can prepare and protect themselves in time-honoured ways. Internal risks include human error, fraud, systems failure, disrupted production, and other risks. Often systems are assumed to be in place to detect and control risk, but inaccurate numbers are sometimes generated for various reasons (Schaefer and Cassidy 2006). Organisations of all types need robust, reliable systems to control risks that arise in all facets of life.

Differences between ERM and traditional risk management were compared by Banham (2004) as shown in Table 1.

Tools of risk management can include creative risk financing solutions, blending financial, insurance and capital market strategies (AIG, as reported by Baranoff 2004). Capital market instruments include catastrophe bonds, risk exchange swaps, derivatives/options, catastrophe equity puts (cat-e-puts), contingent surplus notes, collateralised debt obligations, and weather derivatives.

2.1 *Types of risk*

Stroh (2005) gave a universe of business risk types, used as the headings in Table 2.

This classification was for the healthcare industry, but demonstrates the scope of risks that organisations can face.

2.2 *Current status*

The Conference Board published results of a survey of 271 risk management executives from North America and Europe (Millage 2005). Respondents of organisations with long ERM experience indicated that ERM had significantly added higher levels of value to organisations than those respondents belonging to organisations that had implemented ERM more recently. Benefits cited were better-informed decisions (86% of experienced ERM organisations, 58% of all others), greater management consensus (83% of experienced, 36% of all others), and increased management accountability (79% of experienced, 34% of all others). Those organisations that had fully implemented ERM were better able to accomplish strategic planning, and had a stronger ability to understand and weigh risk tradeoffs.

There has been significant recent research in ERM. Walker *et al*. (2003) reported ERM efforts at five large companies. Kleffner *et al*. (2003) reported the uses of ERM by Canadian risk and insurance management companies. Lynch-Bell (2002) reported results of a survey of 52 companies with respect to risk management practices. Beasley *et al*. (2005) reported survey results of 123 organisations, with the following variables found positively related to ERM implementation: presence of a chief risk officer, board independence, top management support, presence of a Big Four auditor, entity size, and the industries of banking, education, and insurance.

Table 1. Differences between ERM and traditional risk management (Banham 2004).

Traditional risk management	ERM
Risk as individual hazards	Risk viewed in context of business strategy
Risk identification and assessment	Risk portfolio development
Focus on discrete risks	Focus on critical risks
Risk mitigation	Risk optimisation
Risk limits	Risk strategy
Risks with no owners	Defined risk responsibilities
Haphazard risk quantification	Monitoring and measurement of risks
'Risk is not my responsibility'	'Risk is everyone's responsibility'

Table 2. Business risk types (Stroh 2005).

External environment	Business strategies and policies	Business process execution	People	Analysis and reporting	Technology and data
Competitors	Strategy and innovation	Planning	Leadership	Performance management	Technology infrastructure/architecture
Legal and regulatory catastrophic loss	Capital allocation	Process/technology design	Skills/competency	Budgeting/financial planning	Data relevance and integrity
Medical cost/utilisation trends	Business/product portfolio	Technology execution and continuity	Change readiness	Accounting/tax information	Data processing integrity
Customer expectations	Organisation structure	Resource capacity and allocation	Communication	External reporting and disclosure	Technology reliability and recovery
	Organisation policies	Vendor/partner reliance	Performance incentives	Pricing/margin	IT security
		Channel effectiveness	Accountability	Market intelligence	
		Interdependency	Fraud and abuse	Contract commitment	
		Customer satisfaction			
		Regulatory compliance and privacy			
		Knowledge/intellectual capital			
		Change integration			

Stroh (2005) reviewed the process of ERM at United Health Management (UHM). UHM is a large, diversified company dedicated to making the healthcare system work better. HRM serves the healthcare industry with benefits, services, and analytic tools aimed at improving clinical and financial performance. UHM viewed ERM as a discipline embedded within the organisational philosophy, meant to identify business risk factors, assess their severity, quantify them, and mitigate them while capitalising on upside opportunities. A pyramid of risks was given as in Table 3.

ERM was viewed as providing UHM a framework for discipline, a methodology enabling management to effectively deal with uncertainty and associated risks.

3. DEA value at risk

Value-at-risk (VaR) methods provide a new theoretical tool for financial economics-based ERM (Duffie and Pan 1997, Jorion 2007). VaR were established as a response to several major financial disasters in the late 1980s and early 1990s, including the fall of Barings Bank and bankruptcy of Orange County (Jorion 2007). In both instances, large amounts of capital were invested in volatile markets when traders concealed the risk exposure from upper management. VaR allows managers to quantify their risk exposure and thus provides a simple quantitative tool for effective risk management at a portfolio level. Measures based on VaR have been employed as a benchmark, where risk positions across different markets are compared.

Value at risk can be defined as the worst-case expected losses occurred for an investment or portfolio at a given confidence level and time horizon. Suppose the risk exposure of some investment is L. Mathematically, we can express VaR definition in the following equation: $\mathrm{Prob}\{L \le \mathrm{VaR}\} = 1-\alpha$. A rational investor will always like to minimise the worst-case expected losses, which establishes the following optimisation problem:

$$\min\{\phi\} = \min\{\mathrm{VaR}|\mathrm{Prob}\{L \le \mathrm{VaR}\} \geqslant 1-\alpha\}. \tag{1}$$

Table 3. Risks by level (Stroh 2005).

Top level	Strategic business risk	Decompose strategic risks/opportunities Mitigation/acceleration plan Assure leadership that top risks are in sight
2nd level	Market/business environment risk	Internal risk sensing (identify potential issues early and alert management) External risk sensing (peer, industry, market monitoring)
3rd level	Financial performance risk	Identify gaps in management plans to achieve financial targets Test/verify assumptions behind key decisions
4th level	Operational risk	Develop baseline, audit plan to link strategic and tactical risks Provide advisory services to develop operational controls
5th level	Compliance and financial reporting risk	Partner with external audit General and regular financial controls

The standard deviation or volatility of asset returns, σ, is a widely used measure of financial models such as VaR. Volatility σ represents the variation of asset returns during some time horizon in the VaR framework. This measure will be employed in our approach. Monte Carlo Simulation techniques are often applied to measure the variability of asset risk factors (Crouhy *et al.* 2001). We will employ Monte Carlo Simulation for benchmarking our proposed method.

Now we consider combining DEA into the VaR system to develop a new vendor selection model. We assume that there are J suppliers to be evaluated, of which supplier j ($j=1,2,\dots,J$) exhibits random performance behaviour represented by random output benefit-oriented vectors $\tilde{y}_j=(\tilde{y}_{1j},\dots,\tilde{y}_{rj},\dots,\tilde{y}_{sj})$, where $\tilde{y}_{rj}$ ($r=1,2,\dots,s$) has a known probability distribution. For the jth supplier, the joint distribution of ($\tilde{y}_j$) is assumed to be known and determined by historical data on inputs and outputs. Here, we do not consider cost-oriented variables for two reasons: first, cost-oriented data can be transferred into benefit-oriented data in data pre-processing process, and second, in practice, many score-card based data are benefit-oriented, as in our case.

During the vendor evaluation process, preferred vendors are most likely to be the ones resulting in better benefit and less loss than others. Suppose the 0th vendor with performance data $\tilde{y}_0$ is under evaluation. We compare the 0th vendor with a virtual vendor constructed from performance data of all existing vendors, i.e.

$$\sum_{j=1}^{J} \lambda_j \tilde{y}_{rj} \ (r=1,2,\ \dots,s)$$

where λ_j is a non-negative multiplier attached to supplier j. We now define the relative loss as

$$L_{r0}=\frac{\tilde{y}_{r0}}{\sum_{j=1}^{J}\lambda_j\tilde{y}_{rj}}. \tag{2}$$

Applying the above definition into (1) leads to:

$$\begin{aligned} &\max_{\theta,\lambda_j} \theta \\ &\text{s.t.} \qquad \mathrm{P}\left\{\sum_{j=1}^{J}\lambda_j\tilde{y}_{rj}\geq\theta\tilde{y}_{r0}\right\}\geq 1-\alpha, \quad r\in R \\ &\qquad\qquad \lambda_j\geq 0, \quad j=1,\dots,J, \end{aligned} \tag{3}$$

where R is the supplier index set. In the above programming (3), the first constraint is called $(1-\alpha)\%$ chance constrains. This means for any production point

$$\tilde{y}_{rk}=\sum_{j=1}^{J}\lambda_j\tilde{y}_{rj},$$

which satisfied the constrains in (3) we are $(1-\alpha)\%$ sure that $\tilde{y}_{rk}$ is greater than θ times of $\tilde{y}_{r0}$. The scalar α is referred to as the modeller's risk level, indicating the probability measure of the extent to which Pareto efficiency violation is admitted as most α proportion of the time (Li 1998). The higher the value of α, the higher the modeller's risk and the lower the modeller's confidence about the 0th vendor's Pareto efficiency and *vice versa*. At the $(1-\alpha)\%$ confidence level, the 0th supplier is stochastic efficient only if the optimal objective value is equal to one. We call model (3) the 'DEA VaR' model because this model is essentially a simplified version of the stochastic DEA of Li (1998), where both input and output variables are considered.

Taking the output slack variables into account, model (3) is reformulated as follows.

$$\begin{aligned}
&\operatorname*{Max}_{\theta,\lambda_j,s_r^+} \theta + \varepsilon \sum_{r\in R} s_r^+ \\
&\text{s.t.} \qquad \mathrm{P}\left\{\sum_{j=1}^{J} \lambda_j \tilde{y}_{rj} \geq \theta \tilde{y}_{r0}\right\} - s_r^+ = 1-\alpha, \quad r \in R \\
&\qquad\qquad \lambda_j, s_r^+ \geq 0, \quad j = 1\ldots J, \quad r \in R
\end{aligned} \tag{4}$$

where ε is a non-Archimedean infinitesimal.

To transform the stochastic model (4) into a deterministic DEA, chance constrained programming can be employed (Charnes *et al*. 1958, Huang and Li 2001). This is usually done by assuming the following input–output data structure with random disturbances for the jth supplier where the component of any stochastic attributes is determined solely by a single factor ξ:

$$\tilde{y}_{rj} = y_{rj} + b_{rj}\xi, \quad \text{for all } r \in R, \quad j = 1,\ldots,J. \tag{5}$$

Here ξ follows a normal distribution with mean $E(\xi) = 0$ and a finite standard deviation such as a unity value. y_{rj} represents the mean of the rth output $\tilde{y}_{rj}$ and b_{rj} is the associated standard deviation. This assumption greatly facilitates the application of the proposed model in two ways: reducing the number of estimated parameters and transforming our chance constraint-programming problem into a linear programming problem. Based on (5), model (4) can be reduced to the following non-linear programming problem (6):

$$\begin{aligned}
&\operatorname*{Max}_{\theta,\lambda_j} \theta \\
&\text{s.t.} \qquad \sum_{j=1}^{J} \lambda_j y_{rj} + \sigma_r^o(\lambda)\Phi^{-1}(\alpha) \geq \theta y_{r0}, \quad r \in R \\
&\qquad\qquad \lambda_j \geq 0, \quad j = 1\ldots J, \quad r \in R
\end{aligned} \tag{6}$$

where Φ is a standard normal distribution function and $\Phi^{-1}(\alpha)$, its inverse, is the so-called 'fractional function'. To linearise the constraints in the above model into linear constraints, we employ the assumption in (5) to get

$$(\sigma_r^O(\theta,\lambda))^2 = \mathrm{V}\left(\theta\tilde{y}_{r0} - \sum_{j=1}^{J} \lambda_j \tilde{y}_{rj}\right) = \left(\theta b_{r0} - \sum_{j=1}^{J} b_{rj}\lambda_j\right)^2 \tag{7}$$

Applying (7) into (6) leads to:

$$\begin{aligned}
&\operatorname*{Max}_{\theta,\lambda_j} \theta \\
&\text{s.t.} \qquad \sum_{j=1}^{J} \lambda_j y_{rj} + \left|\theta b_{r0} - \sum_{j=1}^{J} b_{rj}\lambda_j\right| \Phi^{-1}(\alpha) \geq \theta y_{r0}, \quad r \in R \\
&\qquad\qquad \lambda_j \geq 0, \quad j = 1\ldots J, \quad r \in R
\end{aligned} \tag{8}$$

The above programming is non-linear deterministic only due to the absolute value of the constraint. It can be easily converted to a linear programming by introducing some new variables. Let $\theta b_{r0} - \sum_{j=1}^{J} b_{rj}\lambda_j = z_r^+ - z_r^-, z_r^+, z_r^- \geq 0$, then

$$\left|\theta b_{r0} - \sum_{j=1}^{J} b_{rj}\lambda_j\right| = z_r^+ + z_r^-. \tag{9}$$

Finally we get the following deterministic linear programming

$$\begin{aligned}
&\underset{\theta,\lambda_j,z_r^+,z_r^-}{\text{Max}} \quad \theta \\
&\text{s.t.} \qquad \sum_{j=1}^{J} \lambda_j y_{rj} + (z_r^+ + z_r^-)\Phi^{-1}(\alpha) \geq \theta y_{r0}, \quad r \in R \\
&\qquad\qquad \theta b_{r0} - \sum_{j=1}^{J} b_{rj}\lambda_j = z_r^+ - z_r^- \\
&\qquad\qquad \lambda_j, z_r^+, z_r^- \geq 0, \quad j = 1 \ldots J, \quad r \in R
\end{aligned} \tag{10}$$

Here Φ is a standard normal distribution function and $\Phi^{-1}(\alpha)$, its inverse, is the so-called 'fractional function'. We also note that our approach from Model (8) leading to (10) is innovative, which is different from Li (1998).

4. Supply chain vendor selection

This section demonstrates utilisation of two main ERM approaches in supply chain vendor selection: Monte Carlo simulation and the proposed DEA VaR approach.

Vendor evaluation is a very important operational decision. There are decisions selecting which vendors to employ, as well as decisions with respect to quantities to order from each vendor. With the increase in outsourcing and the opportunities provided by electronic business to tap world-wide markets, these decisions are becoming ever more complex. The presence of multiple criteria in these decisions has long been recognised. Dickson (1966) identified 23 distinct criteria in various vendor selection problems. Weber *et al.* (1991) found multiple criteria in 47 of the 76 vendor selection articles that they reviewed. Table 4 compares criteria used in 12 studies from the operations research/operations management field considering multiple criteria over the period 1996 through 2006. Price, quality, and response have become endemic.

Table 4. Vendor selection criteria (Wu and Olson 2008).

Criteria	Number of studies using
Price/cost	11
Acceptance/quality	11
On-time response/logistics	11
R&D in technology/innovation/design	7
Production facilities/assets	6
Flexibility/agility	6
Service	4
Management and organisation	2

Other criteria have been used as well, but only one of the 12 studies cited any of these. Stochastic DEA and stochastic dominance model applied through simulation are used to measure the vendor efficiency. The model aims to maximise the efficiency of vendor subject to attaining the desired 'quality', 'price', 'performance', 'facilities/capabilities' levels. In our stochastic DEA model, all the attributes are deemed as outputs since they are normalised as in Moskowitz *et al*. (2000). The process is to (1) identify criteria, (2) identify alternative vendors, (3) select measures, and (4) use a model to rank-order vendors. Our focus will be on measures that are as objective as possible, to include uncertain elements. Alternative models considered in this paper are stochastic dominance, simulation, and stochastic DEA. The hierarchy of criteria used by Moskowitz *et al*. (2000) was used, as shown in Figure 1.

In the past, more emphasis seems to have been placed on managerial and organisational reputation, expertise, and attitude. Some criteria continue to have a moderate presence, such as the availability of adequate facilities, technological innovation, and the ability to provide service. More recent articles place an increased emphasis on flexibility and agility, probably reflecting the increased use of e-commerce, rapid delivery, and more responsive delivery.

Data was taken from Moskowitz *et al*. (2000), providing means and standard deviations for the ratings of nine vendors over all 12 criteria given in Figure 1. We note that this data is used for demonstration of enterprise risk management tools. Practical problems of vendor evaluation under risk and uncertainty can be handled by applying our techniques into data collected following Moskowitz *et al*. (2000). For this data, four vendors (V_2, V_4, V_6, and V_8) were stochastically non-dominated. Our simulation was applied with equal weights, yielding the same results, but additionally providing information on the relative probability of being selected for random sets of relative importance weights for each of the 12 criteria. Ordinal restrictions on weights were also applied, following the relative order of criteria importance given in Moskowitz *et al*. (2000):

$$W_2 > W_1 > W_3 > W_4 > W_5 > W_6 > W_7 > W_{10} > W_8 > W_9 > W_{11} > W_{12}$$

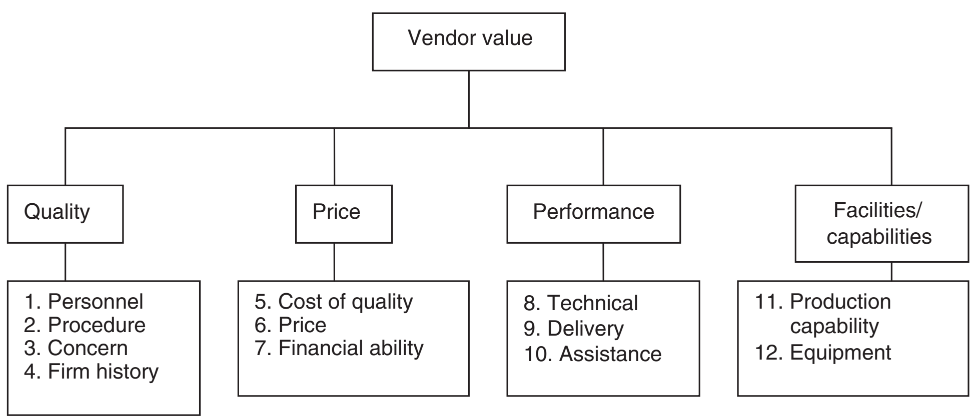

Figure 1. Criteria hierarchy for supply chain vendor evaluation.

Simulation of multiple criteria models is now easily accomplished, using such tools as Crystal Ball, which supports spreadsheets such as EXCEL (Evans and Olson 2005). Simulation can replicate the results of stochastic dominance by assuming a set of weights with ranges and order as specified. Selection is identified by calculating the simulated value function for each of the nine vendors, with the highest value function selected. If enough simulation runs are made, it can reflect any complexities that might be present in a model. Simulation has been applied in fuzzy data mining models (Olson and Wu 2006). The simple multi-attribute rating theory (SMART – Edwards and Barron 1994) model simply bases selection on the rank order of the product of criteria weights and alternative scores over these criteria. The data given in Table 3 of Wu and Olson (2008) can directly be applied in a Crystal Ball model. Using random weights and controlling for random scores (so that equal luck is given to each alternative over each criterion), stochastically non-dominated solutions are the only ones with the possibility of having the greatest score. This in fact was attained in our model. The ordinal weights suggested by Moskowitz *et al.* (2000) were also applied. Table 5 gives the proportion of 1000 simulation runs, yielding probabilities of each alternative being preferred.

The equal weight model confirmed the stochastic dominance results (we achieved the same result as Moskowitz *et al.* 2000). But the simulated multi-attribute model yields more information, showing the probabilities of each alternative vendor being preferred for the data given. Adding more information about relative weights will provide yet more information, as it should. Here, the most probable selection under conditions of random weights with equal probabilities was never selected, as the weights associated with this vendor's strengths were given relatively low importance. While Moskowitz *et al.* (2000) identified V_2 and V_6, Table 5 shows through simulation results that V_4 was also non-dominated with this set of ordinal weights. Vendor alternative V_2 turned out to be the most probable best choice for the ordinal weights given.

4.1 *DEA VaR analysis*

DEA was first introduced in 1978 by Charnes, Cooper and Rhodes (CCR) for efficiency analysis of Decision-making Units (DMU). DEA can be used for modelling operational processes, and its empirical orientation and absence of *a priori* assumptions have resulted in its use in a number of studies involving efficient frontier estimation in both non-profit and in private sectors. DEA has become a leading approach for efficiency analysis in many fields, such as supply chain management (Ross and Droge 2002), business research and

Table 5. Simulation estimates of probability of selection.

Vendor alternative	Equal weights	Ordinal weights
V_1	0.00	0.00
V_2	0.03	0.71
V_3	0.00	0.00
V_4	0.08	0.22
V_5	0.00	0.00
V_6	0.36	0.07
V_7	0.00	0.00
V_8	0.53	0.00
V_9	0.00	0.00

development (Verma and Sinha 2002), petroleum distribution system design (Ross and Droge 2004), military logistics (Sun 2004), and government services (Narasimhan *et al.* 2005). This section applies the DEA VaR model we developed into the above data.

With data extracted from Moskowitz *et al.* (2000) (also refer to Wu and Olson 2008), we assume the same parameter $\alpha_j = \alpha$ all $j = 1, \dots, 9$. We run the DEA model given in with various values for these parameters to see the sensitivity of the results. DEA stochastic efficiency scores of the nine vendors are obtained by running model (13) with different combinations of $\alpha \in \{0.05, 0.1, 0.2, 0.3, 0.4, 0.5\}$. The DEA VaR model is solved nine times, each for one of the alternatives under evaluation. The formulation to compute the efficiency θ_1 for the first vendor is:

$$\begin{aligned} &\text{Max } \theta_1 = \theta \\ &\text{Subject to}: \quad \text{constraint for all variables } r \text{ from 1 to 12} \\ &\qquad\qquad\qquad \lambda_j \geq 0 \quad \text{all } j \text{ from 1 to 9.} \end{aligned}$$

λ_j is defined in model (10) and denote the multiplier attached to the jth supplier. For $r = 2$, the first two constraints are specifically expressed as:

$$\sum_{j=1}^{9} \lambda_j y_{2j} + (z_2^+ + z_2^-)\Phi^{-1}(\alpha) \geq \theta y_{21}$$

and

$$\theta b_{21} - \sum_{j=1}^{J} b_{2j}\lambda_j = z_2^+ - z_2^-,$$

where Φ stands for a cumulative distribution function of the normal distribution and Φ^{-1} indicates its inverse function, and y_{2j} $(j = 1, \dots, N)$ is its second expected output value of the jth supplier. Specifically, they are

$$\begin{aligned} &(80\lambda_1 + 88\lambda_2 + 85\lambda_3 + 90\lambda_4 + 75\lambda_5 + 82\lambda_6 + 82\lambda_7 + 90\lambda_8 + 90\lambda_{19}) \\ &\quad + (z_2^+ + z_2^-)\Phi^{-1}(\alpha) \geq 80\theta \end{aligned}$$

and

$$\begin{aligned} &5.2\theta - (z_2^+ - z_2^-) \\ &\quad = (5.2\lambda_1 + 4.2\lambda_2 + 5.1\lambda_3 + 4.2\lambda_4 + 5.6\lambda_5 + 2.2\lambda_6 + 4.2\lambda_7 + 3.3\lambda_8 + 3.8\lambda_9). \end{aligned}$$

To see the change trend of efficiency with respect to α, we give a plot of the efficiency versus the value of α in Figure 2. This plot shows that the efficiency value given to most suppliers (except V_4) increases as the value of α goes up. This systematic trend is consistent with that in Sueyoshi (2000) and Wu and Olson (2008).

Table 6 documents the stochastic efficiency for each vendor with respect to parameter $\alpha \in \{0.05, 0.1, 0.2, 0.3, 0.4, 0.5\}$. The scalar α reflects the decision maker's risk level and indicates the probability measure of the extent to which Pareto efficiency violation is admitted. As can be seen from Table 6, V_4 is stochastically efficient when a small value of α is used while the efficient alternative vendor shifts to be V_8 when the decision maker's risk level is higher using a larger value of α. Whatever risk level the decision maker uses, the non-dominated supplier is preferred by the simulation selection result in Table 5. Values in

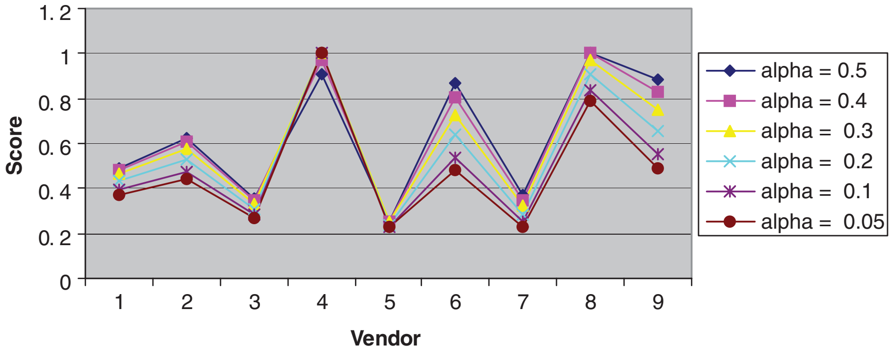

Figure 2. Efficiency scores for different alpha values.

Table 6. DEA VaR results with respect to α.

Scenario	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9
Alpha = 0.5	0.48824	0.62250	0.35470	0.91137	0.25152	0.86458	0.36889	1	0.88675
Alpha = 0.4	0.48300	0.60507	0.34955	0.97119	0.25346	0.80559	0.34965	1	0.82559
Alpha = 0.3	0.46379	0.57250	0.33476	1	0.24910	0.73004	0.32242	0.96891	0.74758
Alpha = 0.2	0.43101	0.52527	0.31064	1	0.23893	0.63830	0.28740	0.90766	0.65307
Alpha = 0.1	0.39299	0.47357	0.28330	1	0.22940	0.54000	0.24934	0.83399	0.55192
Alpha = 0.05	0.37031	0.44394	0.26723	1	0.22678	0.48145	0.22678	0.78886	0.49161

Table 6 also suggest that at the 95% confidence level, the fourth supplier is stochastic efficient and will be selected. Table 6 also provides values for ranking orders of all vendors.

DEA VaR efficiency when the risk level is low, e.g. $\alpha = 0.005$:

$$\mathrm{V}_4 \succ \mathrm{V}_8 \succ \mathrm{V}_9 \succ \mathrm{V}_6 \succ \mathrm{V}_2 \succ \mathrm{V}_1 \succ \mathrm{V}_3 \succ \mathrm{V}_5 \sim \mathrm{V}_7$$

where the symbol '$\succ$' denotes 'is superior to' and '$\sim$' denotes 'is indifferent to'.

DEA VaR efficiency when the risk level is high, e.g. $\alpha = 0.4$:

$$V_8 \succ V_4 \succ V_9 \succ V_6 \succ V_2 \succ V_1 \succ V_7 \succ V_3 \succ V_5.$$

As can be expected, different approaches identify a different non-dominated vendor. Choosing a different risk level affects the result of ranking orders. The same problem occurs in Moskowitz *et al.* (2000) where they identified completely different non-dominated vendors by using random weight assumption and ordinal weight assumption. Under assumption of random weights, Moskowitz *et al.* (2000) identified V_6 and V_8 as non-dominated vendors. The first order dominated vendors are V_1, V_3, V_4, V_7 and V_9. Moskowitz *et al.* (2000) argued that this 'expected' difference is because different approaches, different model assumptions and different criteria for filtering inferior alternatives were employed.

Although there is some difference between these approaches, we achieved many consistent solutions. First, our DEA VaR either term V_4 or V_8 as most efficiency alternative, which is consistent with our simulation result in Section 3, where simulation indicates V_2, V_4, V_6 and V_8 all have potential to be selected as non-dominated vendor.

Second, our DEA VaR models agree that V_3, V_5 and V_7 are frequently been filtered due to their poor performance represented in efficiency value. This verifies the strong diagnosing power in identifying the worst cases. This can be also verified from Figure 2.

5. Conclusions

The importance of risk management has vastly increased in the past decade. Value at risk techniques have become the frontier technology for conducting enterprise risk management. One of the ERM areas of global business involving high levels of risk is global supply chain management. This paper has developed a new approach called 'DEA VaR' for selection of vendors in ERM. This is a simplified version of existing stochastic DEA models. Thus, the main purpose of this paper is to review and present new ERM approaches.

Vendor selection in supply chains by its nature involves the need to trade off multiple criteria, as well as the presence of uncertain data. When these conditions exist, stochastic dominance can be applied if the uncertain data is normally distributed. If not normally distributed, simulation modelling applies (and can also be applied if data is normally distributed).

DEA VaR can help to improve a performance measurement system in supply chain management. When the data is presented with uncertainty, stochastic DEA provides a good tool to perform efficiency analysis by handling both inefficiency and stochastic error. We must point out the main difference for implementing a investment VaR in financial markets such as the banking industry and our DEA VaR used for supplier selection: the underlying asset volatility or standard deviation is typically a managerial assumption due to lack of sufficient historical data to calibrate the risk measure.

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