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Enterprise risk management: small business scorecard analysis

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Enterprise risk management has become an important consideration in all aspects of business, including production planning. Business risk scorecards are important tools to monitor the performance of organisations. This article demonstrates the value of business scorecards as a means to monitor organisational performance with respect to risk management. A small bank credit loan case is used to make this demonstration. The relevance of small business scorecards to operations and supply chain management as a means to implement enterprise risk management is discussed.

Keywords: enterprise risk management; small business scorecard (SBS); statistics; credit; operations

1. Introduction

Production planning and control involves the need to consider risk in a systematic manner. Enterprise risk management (ERM) has become important in all aspects of organisational operations (Olson and Wu 2008a,b). There are a number of quantitative tools available to support risk planning. An important tool is business scorecards (Kaplan and Norton 1992, 2006). Olhager and Wikner (2000) reviewed a number of production planning and control tools, where scorecards are deemed as the most successful approach in production planning and control performance measurement. Various forms of scorecards, e.g. company-configured scorecards and/or strategic scorecards, have been suggested to build into the business decision support system or expert system in order to monitor the performance of the enterprise in the strategic decision analysis (Al-Mashari *et al.* 2003, Wu *et al.* 2008). This article demonstrates the value of small business scorecards with a case from a real operation (in this case a bank).

Contingency management has been widely systematised in the military, although individual leaders have practised various forms for millennia. Various stakeholders pertaining to an organisation have potentially different objectives and make the company leadership complicated, which can lead to a lot of conflicts in order to satisfy a variety of stakeholder demands. Scenario analysis has been included in systematic organisational planning. This provides executives

with a means of understanding what might go wrong and opportunities to prepare reaction plans. 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 can be used to reduce core organisational risk. Because risk is inherently part of strategy, Dickinson suggested that it needs to be measured in terms of organisational objectives.

While risk needs to be managed, taking risks is fundamental for doing business. Profit by necessity requires accepting some risk (Alquier and Tignol 2006). ERM provides tools to rationally manage these risks. Various statistic models, e.g. reject inference scorecards have been presented for performance evaluation in the past (Crook and Banasik 2004). Scorecards have been successfully associated with risk management at Mobil, Chrysler, the US Army and numerous other organisations (Kaplan and Norton 2006). This article aims to address ERM quantitative models using business scorecards in a

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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 & 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'

small business credit analysis problem. Thus we are not presenting a new statistic scorecard model, but rather report an application of business scorecards to demonstrate ERM tools reported in the literature. This demonstration provides how quantitative models are implemented in a good ERM case, i.e. small business credit risk.

The rest of this article is organised as follows. Section 2 of this article discusses ERM concepts, the status and some links with management of operations. Section 3 presents small business scorecard analysis, to include data, computation and comparison results. Section 4 concludes this article.

2. ERM concepts, the status and operations

Enterprise risk management provides the methods and processes used by business institutions to manage all risks and seize opportunities to achieve their objectives. ERM began with a focus on financial risk, but has expanded its focus to accounting as well as all aspects of organisational operations in the past decade. Enterprise risk can include a variety of factors with potential impact on an 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 generated for various reasons (Schaefer *et al.* 2006).

The recent focus on accounting risk has arisen in the past decade. A number of traumatic events such as 11 September 2001 and business scandals to include Enron and WorldCom have prompted business organisations in different industries to examine their operations risk exposures to the public, employees and capital

investments. On the other hand, adopting ERM has been one of the best strategies to prepare for the new risk-based governance from the regulators such as Basel II in Europe (Basel II 2004) and similar regulations in the US Sarbanes–Oxley Act (Olson and Wu 2008a). This creates another important incentive for companies to use ERM as a means to verify operations risk, e.g. the risk aspects of a proposed design and safety-conscious factors concerning system changes. All organisations need robust, reliable systems to control risks that arise in all facets of their operations.

We show in Table 1 the differences between ERM and traditional risk management (for details of this comparison, please refer to Banham (2004)).

ERM brings a systemic approach to risk management. This systemic approach provides more systematic and complete coverage of risks (far beyond financial risk, for instance). ERM provides a framework to define risk responsibilities, and a need to monitor and measure these risks. That is where business scorecards provide a natural fit – measurement of risks that are key to the organisation.

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. Current status

Recently, there has been significant 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.* (2004) reported survey results of 123 organisations, with the following

Table 2. 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)
3rd level	Financial performance risk	External risk sensing (peer, industry and market monitoring) Identify gaps in management plans to achieve financial targets
4th level	Operational risk	Test/verify assumptions behind key decisions Develop baseline, audit plan to link strategic and tactical risks
5th level	Compliance and financial reporting risk	Provide advisory services to develop operational controls Partner with external audit General and regular financial controls

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. Researchers believe that ERM is an important source of competitive advantage for organisations demonstrating a strong ERM capability and discipline (Stroh 2005).

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 did 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 completely implemented ERM were able to accomplish strategic planning, and had a stronger ability to understand and weigh risk tradeoffs.

2.2. ERM and operations

Enterprise risk management has also motivated a great deal of operational level studies in production planning and control, to include specific domain problems such as supply, transformation and distribution operations in energy and health sectors. For example, Pongsakdi *et al.* (2006) study purchase of the crude when risk and return are to be tradeoff and decide on the production level of different products given forecasts of demands. Liu and Sahinidis (1996) studied a two-stage stochastic programming approach for process planning under uncertainty. Wang and Liang (2005) developed an

interactive possibilistic linear programming model to systematically plan the multi-product production when risks are associated with forecast demand, related operating costs and capacity. Barbaro and Bagajewicz (2004) proposed a methodology to combine financial risk management with a two-stage stochastic programming for planning under uncertainty. Stroh (2005) reviewed the process of ERM at United Health Management (UHM). These research and many others have promoted the application of numerous traditional quantitative techniques into ERM, which include, for example, linear and non-linear programming, stochastic models, fuzzy set theory (Liu and Sahinidis 1997), fault tree analysis (Schlechter 1996) and scorecard (Papalexandrisa *et al.* 2005).

We employ the study from Stroh (2005) as a concrete example to illustrate ERM in the UHM operations. UHM is a large, diversified company dedicated to make 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 is given in Table 2.

ERM was viewed as providing UHM with a framework for discipline, a methodology enabling management to effectively deal with uncertainty and associated risks. We demonstrate the application of ERM tools to another important operation, i.e. financial operation, using small business scorecard analysis.

3. Small business scorecard analysis

This section discusses computational results on various scorecard performances that are currently being used

in a large bank. This bank uses various ERM performance measures to validate small business scorecard. Because scorecards have a tendency to deteriorate over time, it is appropriate to examine how well they are performing and to examine any possible changes in the scoring population. A number of statistics and analyses will be employed to determine if the scorecard is still effective.

3.1. ERM performance measure

Some performance measures for enterprise risk modelling are reviewed in this section. They are used to determine the relative effectiveness of the scorecards. For a detailed discussion of these measures, readers can refer to Olson and Wu (2008a). There are four measures reviewed: the Divergence, Kolmogorov–Smirnov (KS) Statistic, Lorenz Curve and the Population stability index. ‘Divergence’ is calculated as the squared difference between the mean score of good and bad accounts divided by their average variance. The dispersion of the data about the means is captured by the variances in the denominator. The divergence will be lower if the variance is high. A high divergence value indicates that the score is able to differentiate between good and bad accounts. Divergence is a relative measure and should be compared to other measures. ‘KS Statistic’ is the maximum difference between the cumulative percentage of goods and cumulative percentage of bads for the population rank-ordered according to its score. A high KS value shows it is very possible that the good ones receive high scores and the bad ones receive low scores. The maximum possible KS statistic is unity. ‘Lorenz Curve’ is the graph that depicts the power of a model capturing bad accounts relative to the entire population. Usually, three curves are depicted: a piecewise curve representing the perfect model which captures all the bads in the lowest scores

range of the model, the random line as a point of reference indicating no predictive ability and the curve lying between these two capture the discriminant power of the model under evaluation. ‘Population stability index’ measures a change in score distributions by comparing the frequencies of the corresponding score-bands, i.e. it measures the difference between two populations. In practice, one can judge there is not real change between the populations if an index value is no larger than and a definite population change if index value is greater than 0.25. An index value between 0.10 and 0.25 indicates some shift.

3.2. Data

Data are collected from the bank’s internal database. ‘Bad’ accounts are defined into two types: ‘Bad 1’ indicating overlimit at month-end, and ‘Bad 2’ referring to those with 35 days since last deposit at month-end. All non-bad accounts will be classified as ‘Good’. We split the population according to credit limit: one for credit limit less than or equal to \$500,000 and the other for credit limit between \$50,000 and \$100,000. Data are gathered from two time slots: observed time slot and validated time slot. Two sets (denoted as Set1 and Set2) are used in the validation. Observed time slots are from August 2002 to January 2003 for Set1 and from September 2001 to February 2002 for Set2, respectively. While this data is relative dated, the system demonstrated using this data is still in use, as the bank has found it stable, and they feel that there is a high cost in switching. Validated time slot are from February 2003 to June 2003 for Set1 and from March 2002 to July 2002 for Set2, respectively. All accounts are scored on the last business day of each month. All non-scored accounts will be excluded from the analyses.

Table 3 gives the bad rates summary by line size for both sets while Table 4 reports the score

Table 3. Bad loan rates by loan size.

Limit	<i>N</i>	No. Bads	Bad rate (%)	<i>N</i>	No. Bads	Bad rate (%)
Bad loans 1 January 2003 (Set1)			Bad loans 2 January 2003 (Set1)			
≤\$50M	59,332	5022	8.46	61,067	1127	1.85
\$50–\$100M	6777	545	8.04	7000	69	0.99
Total	66,109	5567	8.42	68,067	1196	1.76
Bad loans 1 February 2002 (Set2)			Bad loans 2 February 2002 (Set2)			
≤\$50M	61,183	5790	9.46	63,981	1791	2.80
\$50–\$100M	6915	637	9.21	7210	88	1.22
Total	68,098	6427	9.44	71,191	1879	2.64

Note: Bad 1: Overlimit; Bad 2: 35 + Days since last deposit and overlimit.

distribution for both sets, including the Beacon score accounts. From Table 3, we can see that in both sets, although the number of Bad 1 accounts is a bit less than that of Bad 2 accounts, it is still a pretty balanced data. The bad rates by product line size are less than 10%. The bad rates decreased with respect to time by both product line and score band, which can be seen in Tables 3 and 4. For example, for accounts less than or equal to 50M dollars, we can see from the third row of Table 3 that the bad rate decreased from 9.46% and 2.80% in February 2002 to 8.46% and 1.85% in January 2003, respectively.

3.3. Results and discussion

Computation is done in two steps: (1) score distribution and (2) performance validation. The first step examines the evidence of a score shift. This population consists of the four types of business line of credit (BLOC) products. The second step examines measures how well it can predict the bad accounts within a 5-month period. We will apply risk measures in Section 3.1 in second step. This population contains only one type of BLOC accounts.

3.3.1. Score distribution

Figure 1 depicts the population stability indices values from January 2001 to June 2003. The values of indices for the \$50,000 and \$100,000 segments show a steady increase with respect to time. The score distribution of the data set is becoming more unlike the most current population as time spans. Yet, the indices still remain below the benchmark of 0.25 that would indicate a significant shift in the score population.

The upward trend is due to two factors: time on books of the accounts and credit balance. A book of

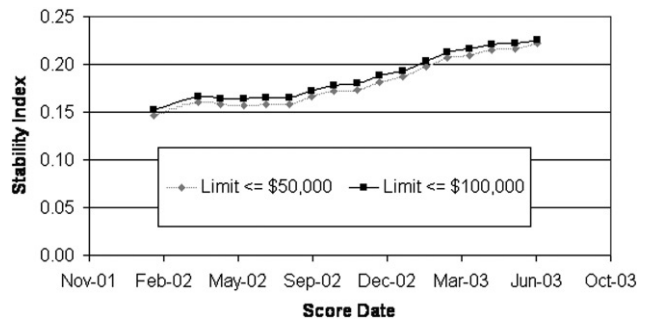


Figure 1. Population stability indices (January 2002–June 2003).

Table 4. Score statistical summary.

Score band	N	Bad	Bad rate (%)	N	Bad	Bad rate (%)
Bad 1 January 2003 (Set1)				Bad 2 January 2003 (Set1)		
0	1210	125	10.33	1263	27	2.14
1–500	152	58	38.16	197	27	13.70
501–550	418	117	27.99	508	49	9.65
551–600	1438	350	24.34	1593	109	6.84
601–650	4514	858	19.01	4841	194	4.01
651–700	11,080	1494	13.48	11,599	321	2.77
701–750	18,328	1540	8.40	18,799	312	1.66
751–800	21,083	888	4.20	21,356	149	0.70
≥800	9096	262	2.88	9174	35	0.38
Beacon	12,813	769	6.00	13,054	328	2.51
Total	80,132	6461	8.06	82,384	1551	1.88
Bad 1 February 2002 (Set2)				Bad 2 February 2002 (Set2)		
0	1840	215	11.74	215	1840	85.60
1–500	231	92	39.83	92	231	25.22
501–550	646	189	29.26	189	646	34.18
551–600	2106	533	25.30	533	2106	39.26
601–650	5348	1078	20.15	1078	5348	49.43
651–700	11,624	1641	14.12	1641	11,624	14.12
701–750	18,392	1647	9.00	1647	18,392	9.00
751–800	20,951	969	4.63	969	20,951	4.63
≥800	8800	278	3.16	278	8800	3.16
Beacon	17,339	1349	7.78	1349	17,339	7.78
Total	87,277	7991	9.15	7991	87,277	9.15

the account refers to a record in which commercial accounts are recorded. First, as the portfolio ages, more accounts will be assigned lower values (i.e. less risky) by the variable time on books of the accounts, thus contributing to a shift in the overall score. Second, more and more accounts do not have a credit balance as time goes. As a result, more accounts will receive higher scores to indicate riskier behaviour.

The shifted score distribution indicates that the population used to develop the model is different from the most recent population. As a result, the weights that had been assigned to each characteristic value might not be the one most suitable for the current population. Therefore, we have to conduct the following performance validation computation.

3.3.2. Performance

To compare the discriminate power of the SBB scorecard with the credit bureau scorecard model, we depict the Lorenz Curve for both ‘Bad 1’ and ‘Bad 2’ accounts in Figures 2 and 3. From both Figures 2 and 3, we can see that the SBB model still provides an effective means for discriminating the ‘good’ from ‘bad’ accounts and that the SBB scorecard captures bad accounts much more quickly than the Beacon score. Based on the ‘Bad 1’ accounts in January 2003, SBS captures 58% of bad accounts, and outperforms the Beacon value of 42%. One of the reasons for

Beacon model being bad in capturing bad accounts is that the credit risk of one of the owners may not necessarily be indicative of the credit risk of the business. Instead, a Credit Bureau scorecard based on the business may be more suitable.

Table 5 reports various performance statistic values for both ‘Bad 1’ and ‘Bad 2’ accounts. Two main patterns are found. First, the Divergence and KS score values produce consistent results as Lorenz Curve did. For both ‘Bad 1’ and ‘Bad 2’, the SBB scorecard performs better than the bureau score in predicting a bad account. Second, SBS based on both bad accounts possibly experience performance deterioration. Table 5 shows that all performance statistic based on the January 2003 data are worse than those of the February 2002 period. For example, the ‘Bad 1’ scorecard generates KS statistic scores of 78 and 136 for January 2003 and February 2003, respectively. The ‘Bad 2’ scorecard generates KS statistic scores of 233 and 394 for both periods.

Table 6 gives performance statistic values for both credit lines, i.e. accounts with credit limit less than or equal to \$50M and between \$50M and 100M. This table shows a comparison between accounts with a limit of \$50M and those with limits between \$50M and 100M. Two main patterns are found. First, the small business scorecards perform well on both, and outperform the Beacon score on both segments. Second, both scorecards, especially the small business scorecard, perform better on ‘Bad 2’ accounts. The main reason is that ‘Bad 2’ definition specifies a more severe degree of delinquency and the difference between the good and bad accounts is more distinct.

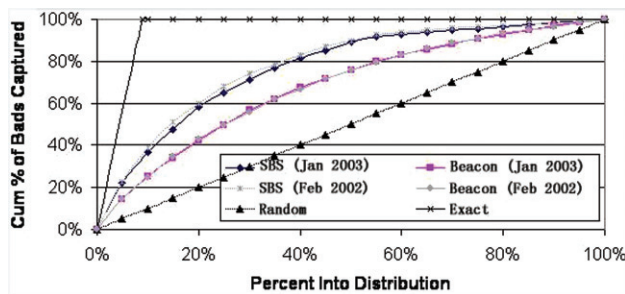


Figure 2. Lorenz Curve for ‘Bad 1’ accounts.

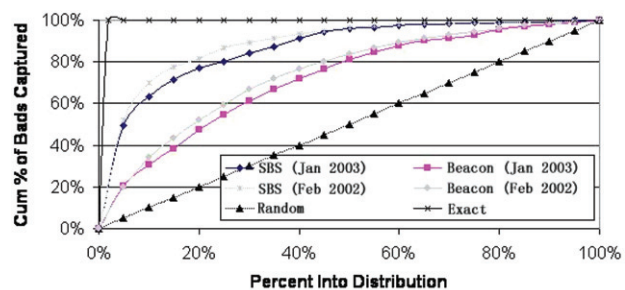


Figure 3. Lorenz Curve for ‘Bad 2’ accounts.

4. Conclusions

The importance of risk management has vastly increased in the past decade. One of the areas of global business involving high levels of risk is global supply chain management. ERM advances the most recent trend in the area of risk management. This article reviewed the state-of-the-art tools in ERM. Various ERM performance measures are applied to validate small business scorecards in a bank. Computation results indicate that there is evidence for a shifting score distribution utilised by the scorecard. However, the scorecard still provides an effective means to predict ‘bad’ accounts.

Business scorecards have been widely applied in general, but not specifically to ERM. This article demonstrates how the business scorecard can be applied to evaluate the risk management posture of a particular organisation. The demonstration is

Table 5. Performance statistic for both 'Bad 1' and 'Bad 2' accounts.

Statistic	SBS	Beacon	SBS	Beacon	SBS	Beacon	SBS	Beacon
	(Janu 2003)	(Jan 2003)	(Feb 2002)	(Feb 2002)	(Jan 2003)	(Jan 2003)	(Feb 2002)	(Feb 2002)
No. good	60,542	60,542	61,671	61,671	66,871	66,871	69,312	69,312
Mean good	108.89	738.71	127.3	734.67	137.4	734.28	171.81	729.23
Std. good	172.74	60.18	203.26	63.53	221.22	62.78	284.21	66.66
	'Bad 1' accounts				'Bad 2' accounts			
No. Accounts	5567	5567	6427	6427	1196	1196	1879	1879
Mean score	344.9	693.13	439.63	685.79	699.82	678.03	995.65	663.2
SD	321.53	69.45	387.24	73.27	570.77	75.42	756.34	76.08
Bad rate	8.42%	8.42%	9.44%	9.44%	1.76%	1.76%	2.64%	2.64%
Divergence	0.836	0.492	1.02	0.508	1.688	0.657	2.079	0.852
KS	78	726	136	716	233	726	394	707

Table 6. Performance statistics for both credit lines.

Credit line	Limit ≤ \$50M				Limit \$50–100M			
	SBS	Beacon	SBS	Beacon	SBS	Beacon	SBS	Beacon
Statistic	(Jan 2003)	(Jan 2003)	(Feb 2002)	(Feb 2002)	(Jan 2003)	(Jan 2003)	(Feb 2002)	(Feb 2002)
Good								
No. accounts	47,682	47,682	48,539	48,539	6232	6232	6278	6278
Mean	116.12	737.77	138.80	733.12	115.13	752.18	125.52	752.64
Std.	177.34	59.12	213.62	62.52	161.93	54.61	174.07	55.86
Bad								
No. accounts	4393	4393	5226	5226	545	545	637	637
Mean score	347.40	695.10	461.06	686.03	345.82	715.80	398.05	711.95
SD	314.69	65.68	391.94	71.87	285.01	68.35	310.59	62.28
Performance								
Bad rate	8.44%	8.44%	9.72%	9.72%	8.04%	8.04%	9.21%	9.21%
Divergence	0.820	0.466	1.042	0.489	0.991	0.346	1.172	0.473
KS	78	726	136	717	125	735	162	742

specifically for a bank, but other organisations could measure appropriate risk elements for their circumstances. Business scorecards offer the flexibility to include any type of measure key for production planning and operations of any type of organisation.

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