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RESEARCH ARTICLE

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A multicriteria discrimination approach for the credit rating of Asian banks

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Abstract In this paper we develop a multicriteria decision aid model, to investigate whether it is possible to replicate the credit ratings of Fitch on Asian banks using publicly available data. The model is developed with the Multi-group Hierarchical DIScrimination (MHDIS) approach, following a tenfold cross validation procedure. Five financial variables are selected from a list of nineteen ones through factor analysis. An additional set of five non-financial variables covering ownership, corporate governance, auditing, strength of bank's franchise and its banking environment is also being used. The results show that equity/customer and short term funding, net interest margin and return on average equity are the most important financial variables. The number of shareholders, the number of subsidiaries and the banking environment of the country in which the banks operate are the most important non-financial ones. In terms of classification accuracies, the results show that the MHDIS model can replicate the credit ratings of Fitch with a satisfactory accuracy and is more efficient than discriminant analysis and ordered logistic regression that are used for comparison purposes.

Keywords Asia · Banks · Credit ratings · Fitch · Multi-criteria

JEL Classification Numbers C63 · G21

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1 Introduction

The large number of bank failures in the later 1980s and early 1990s in the US and the recent Asian crisis in 1997–1998 have shown that banks operating in free market economies can, like any non-financial firm, fail. There is however an important difference between the failure of a bank and a non-financial firm. While the collapse of even huge non-financial firms is less likely to endanger a whole economy, bank insolvencies can result in systemic crises which have adverse consequences for the economy as a whole[1] or as experienced recently (Latin America and Asia) have a quick impact worldwide. Therefore, not surprisingly the financial condition of banks has been recognized as a matter of special interest for numerous stakeholders such as governments, investors and depositors, and has become subject to prudential supervision.

The Basel Committee's new capital adequacy framework (also known as Basel II) is another step towards more efficient banks' supervision. One fundamental innovation under Basel II is the use of credit ratings to provide a more refined measure of banks' credit risk exposure.[2] The new framework allows banks to adapt one of the following approaches. The standardized approach or external ratings approach allows banks to calculate capital charges based on broad groupings of the external ratings assigned by a recognized credit rating agency. The internal ratings based (IRB) relies on banks' internal risk assessments which requires banks to measure risk and manage their portfolios by breaking credit risk into its constituent elements and dealing with each in turn. As a result of these changes, there has been an increased interest in the role of credit agencies and especially on the three agencies that currently dominate the industry, Moody's, Standard and Poor's, and Fitch.

The purpose of the present study is to investigate whether it is possible to develop a multicriteria decision aid model to replicate the credit ratings of Fitch on Asian banks, by using publicly available data.

We focus on Fitch because it is considered more specialized than the other two large agencies, with a major part of its business focusing on the rating of banks. Especially after its merger with Thomson BankWatch (TBW), on December 2000, Fitch now assigns over 1,000 international bank ratings worldwide and is considered the leading bank credit rating agency in terms of coverage, with a dominant market share in emerging markets such as Asia, Africa and Middle East, Central and Eastern Europe and Latin America.

Furthermore, we focus on Asian banks because, as Sherman and Neale (2002) mentioned, Asian banks will have to consider whether to use the standardized or the IRB approach. The advantage of the IRB approach is that banks can use internal credit expertise and historical knowledge derived from defaults and recoveries. However, there are several requirements that should be met to implement the IRB

[1] Caprio and Klingebiel (2003) provide information on 117 systemic banking crises (defined as much or all of bank capital being exhausted) that have occurred in 93 countries since the late 1970s and 51 borderline and smaller (nonsystemic) banking crises in 45 countries during that period. The loss and costs that arise either from corporate restructuring or recapitalization and restructuring of the financial system are huge, in many cases 10–20% of GDP and occasionally as much as 40–55% of GDP.

[2] For more detailed discussions of the new capital adequacy framework, see Basel Committee on Banking Supervision (1999, 2001, 2003, 2004).

approach, regarding the technical aspects of this approach and the data that should be used. Thus, even large banks may face difficulties in implementing the IRB approach. The situation may be worse in Asia where banks are information-poor compared to those in the OECD countries, making the required statistical analysis, both historical and current, quite difficult (Sherman and Neale 2002). Obviously, the IRB approach is appropriate for banks with sophisticated risk measurement and management systems that can demonstrate robust and appropriate internal risk scoring system. Therefore, developing the risk rating systems and infrastructure required within an IRB bank could pose challenges for a number of Asian institutions, most of which are in the early stages of building up their loss databases, developing ratings models and improving the integrity of their risk management systems (Marshall et al. 2005). Consequently, for many Asian banks and bank regulators that are not ready to use an IRB system, it might be more appropriate to follow an external ratings approach.

Despite a fair number of studies that have modeled commercial paper ratings (Peavy and Edgar 1983, 1984; Chandy and Duett 1990) and bonds ratings (Horrigan 1966; Pinches and Mingo 1973; Kaplan and Urwitz 1979; Belkaoui 1983; Kim 1993; Manzoni 2004; Huang et al. 2004), not much attention has been given to the examination of individual firms ratings, known as counterparty ratings. Although some studies examine the ratings assigned to non-financial firms by local credit agencies (e.g. Laitinen 1999; Doumpos and Pasiouras 2005) evidence on the counterparty ratings assigned to banks by one of the large agencies is quite limited. In a relatively recent study, Poon et al. (1999) employed ordered logistic regression to examine the individual financial strength ratings assigned by Moody's in a sample of 130 banks in 1997. We differentiate our study from Poon et al. (1999) in several respects.

First, we employ a multicriteria decision aid (MCDA) methodology, namely MHDIS (multi-group hierarchical discrimination) for the development of the model and compare it with discriminant and ordered logistic regression. MHDIS is well suited for credit risk modeling for several reasons. First, in credit risk modeling, groups are defined in an ordinal way, in the sense that firm classified into a low risk group is preferred to a firm classified into a high risk group (in terms of its probability of default). Traditional statistical classification methods as well as popular machine learning techniques (e.g. neural networks, rule induction algorithms and decision trees) cannot cope with this kind of information. Second, MHDIS is not based on statistical assumptions that often cause problems to the application of statistical methods,[3] such as the normality of the variables or the group dispersion matrices (e.g. discriminant analysis) and is not sensitive to multicollinearity or outliers (e.g. logit analysis). Third, it can easily incorporate qualitative data. Finally, it is well suited to problems with more than two ordered groups, because

[3] Barniv and McDonald (1999) summarize some of the problems related to discriminant, logit and probit that were mentioned in previous studies. Logit and Probit are sensitive to: (a) data properties, such as departure from normality of financial variables (Frecka and Hopwood 1983; Richardson and Davidson 1984; Hopwood et al. 1988); (b) overall small sample size (Noreen 1988; Stone and Rasp 1991); (c) multicollinearity (Aldrich and Nelson 1984; Stone and Rasp 1991). The basic assumptions of discriminant analysis (DA) such as normality, symmetry and equal covariance matrices are also usually violated. Hopwood et al. (1998) point out that DA is generally sensitive to departure from normality and both logit and probit analyses are sensitive to extreme non-normality.

it follows a hierarchical/stepwise discriminating procedure that distinguishes the groups progressively, starting by discriminating the first group from all the others, and then proceeds to the discrimination between the alternatives belonging into the other groups. In this way, the method enables the analysis of the relative importance of the variables for each group of observations.

Second, while Poon et al. (1999) have developed models to explain the ratings they have not examined whether it is possible to replicate them. Although they provide average classification accuracies, these refer to in-sample accuracies, that are usually upward biased, and they have not tested the out-of-sample performance of the models. In the present study, we follow a tenfold cross validation that provides a more accurate test of the classification ability of the models.

Third, we focus on a more recent period that is after the Asian crisis as well as the release of the proposal for Basel II. Fourth, we focus on the rating of Asian banks. Finally, we examine the Fitch individual bank ratings in contrast to Poon et al. (1999), which examined Moody's bank financial strength ratings.

The rest of the paper is as follows. Section 2 describes the sample used and Fitch individual bank ratings. Section 3 outlines the process for the selection of the variables, while Sect. 4 describes the employed multicriteria decision aid. Section 5 presents the empirical results, and finally Sect. 6 discusses the concluding remarks and some directions for future research.

2 Sample

Our sample includes the universe of commercial banks operating in the main South and Southeastern Asian countries for which financial data and Fitch individual bank ratings were available in Bankscope database of Bureau van Dijk's company. That is 153 banks. The ratings correspond to October 2004, while the financial data correspond to end 2003 or March 2004. We focus only on commercial banks to avoid comparison problems between various types of banks.[4] Although Fitch usually relies on consolidated accounts, in many cases it also analyses both the consolidated and the unconsolidated figures (Le Bras and Andrews 2004). Since consolidated statements refer to the banking group as a total, while the unconsolidated ones to the bank as individual unit, we also examine unconsolidated financial statements in addition to consolidated ones for 62 banks, resulting in a total sample of 215 observations. These observations come from 9 markets as follows: China (22), India (36), Japan (42), Hong Kong (25), Korea (20), Malaysia (20), Singapore (5), Taiwan (30), Thailand (15).

The Fitch Individual bank rating is based on A to E scale and represents Fitch's view on the likelihood that the bank will fail, and therefore require support to prevent it from defaulting.[5] Fitch may also assigns the following intermediate ratings: A/B, B/C, C/D and D/E. Table 1 presents the definitions of Fitch individual ratings.

[4] As Le Bras and Andrews (2004) mention in Fitch's 2004 "Bank rating methodology" report, while the basic analytical approach followed in all types of banks (e.g. retail, investment, mortgage, co-operative, savings, private) is the same, there are specificities relating to each type of institution which need to be dealt within in more detail.

[5] Fitch's individual bank ratings does not take account of government of shareholder support, but instead utilizes a separate support rating which rates the strength and likelihood of external support using a 1–5 scale.

Table 1 Definitions of Fitch's Bank Individual ratings

Rating	Definition
A	A very strong bank. Characteristics may include outstanding profitability and balance sheet integrity, franchise, management, operating environment or prospects.
B	A strong bank. There are no major concerns regarding the bank. Characteristics may include strong profitability and balance sheet integrity, franchise, management, operating environment or prospects.
C	An adequate bank, which, however, possesses one or more troublesome aspects. There may be some concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects.
D	A bank, which has weaknesses of internal and/or external origin. There are concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects. Banks in emerging markets are necessarily faced with a greater number of potential deficiencies of external origin.
E	A bank with very serious problems, which either requires or is likely to require external support.
A/B, B/C, C/D, and D/E	Gradations that may be used among the five ratings.

Table 2 Observations by country and rating scale

Country	Rating Category					
	A and A/B	B and B/C	C and C/D	D and D/E	E	Total
China	0	0	0	16	6	22
India	0	0	11	23	2	36
Japan	0	2	8	12	20	42
Hong Kong	4	11	10	0	0	25
Korea	0	4	12	4	0	20
Malaysia	0	4	11	3	2	20
Singapore	0	5	0	0	0	5
Taiwan	0	5	13	8	4	30
Thailand	0	0	4	11	0	15
Total	4	31	69	77	34	215

In the present study, we group banks into the five main categories from A to E, without consideration of the gradations that may be used among them. For example our first set of banks includes those with A and A/B. Similarly, the second set of banks includes those with B and B/C and so on. There are two reasons for doing this. First, it restricts our attention on the basic categories, which are, probably of greater significance. Second, it helps to reduce the occurrences of rating categories with few observations. Table 2 presents the observations by country and rating category. As can be seen only 4 out of the 215 observations were assigned A or A/B rating, that is not surprisingly, since these ratings are only given to very strong banks with outstanding characteristics. On the opposite, banks with E rating that either require or are likely to require external support represent 16% of the total observations in sample. The majority of observations are assigned ratings between C and D/E, accounting for 68% of total observations in sample.

Table 3 List of financial variables available for the analysis

	Variable	Category
TCR	Total capital ratio	Capital strength
EQAS	Equity/tot assets	Capital strength
EQLOAN	Equity/net loans	Capital strength
EQFUND	Equity/customer and short term funding	Capital strength
CAPFUND	Cap funds/customer and short term funding	Capital strength
NIM	Net interest margin	Profit efficiency
REVAS	Net interest revenue/average assets	Profit efficiency
OPINCAS	Other operating income/average assets	Profit efficiency
EXPAS	Non interest expenses/average assets	Cost Efficiency
COST	Cost to income ratio	Cost Efficiency
ROAA	Return on average assets	Profit efficiency
ROAE	Return on average equity	Profit efficiency
REP	Recurring earning power	Profit efficiency
LOANAS	Net loans/tot assets	Liquidity
LOANCUST	Net loans/customer and short term funding	Liquidity
LOANDEP	Net loans/tot deposits and borrowings	Liquidity
LIQCUST	Liquid assets/customer and short term funding	Liquidity
LIQDEP	Liquid assets/tot deposits and borrowings	Liquidity
LOGAS	Log of total assets	Size

3 Variables selection

Le Bras and Andrews (2004) point out that during the analysis of banks Fitch concentrates on the following issues: credit and market risk, funding and liquidity, capital, securitization, performance/earnings, market environment and planning, management and strategy, corporate governance, ownership and audit. We therefore consider various financial and non-financial variables for the development of the model.

3.1 Financial variables

In the present setting that examines banks from various Asian countries, the need for comparable data among countries sets restrictions on the type of financial variables one can use. Therefore to minimize possible bias arising from different accounting practices, broad variable definitions as provided by Bankscope are used.[6] An additional variable, the logarithm of total assets (converted in US dollars to allow comparisons across countries) is employed to measure banks' size. Table 3 presents the 19 financial variables that were initially considered on the basis of data availability.

Prior to the development of the models factor analysis is used to identify any multicollinearity among the financial variables and reduce their number. The results show that there are five factors, with eigenvalues higher than 1, explaining 83% of the total variance in sample. Table 4 presents the factor loadings for the considered financial variables in the extracted factors that were used to select a limited set of financial variables. More detailed, five financial variables are finally selected,

[6] The global format of Bankscope contains standard ratios, which can be compared across countries and cover the main categories of: asset quality, capital, operations (profit and cost efficiency) and liquidity.

Table 4 Factor Analysis

Financial Variables	Factors				
	1	2	3	4	5
EQFUND	**0.9770**				
TCR	0.9710				
EQLOAN	0.9490				
CAPFUND	0.8790				
EQAS	0.8600				
NIM		**0.9430**			
REVAS		0.9420			
REP		0.7580			
LOGAS					
LIQDEP			**0.8790**		
LIQCUST			0.8440		
OPINCAS			0.6540		
LOANDEB				**0.8750**	
LOANCUST				0.8580	
LOANAS				0.7690	
ROAE					**0.8720**
ROAE					0.8580
EXPAS					
COST					

Notes: *1* Empty entries indicate factor loadings lower than 0.65 (in absolute terms). *2* With bold are the financial variables with highest loadings in each factor that were finally selected. *3* Variables are defined in Table 3

each one of them being the one with the highest loading in each factor. These are EQFUND, NIM, LIQDEP, LOANDEP, and ROAE.

3.2 Non-financial variables

In addition to the five financial variables discussed above, five non-financial ones are also used. These are the auditor's opinion on banks' financial statements (AUDIT), the number of subsidiaries (SUBS), the number of institutional shareholders (OWNERS), the Heritage Banking and Finance score (BENV), and whether the bank is listed or not in a stock exchange (STEXCH).

While the rating process of Fitch does not include an audit of bank's financial statements, it does consider accounting policies and the extent to which it accurately reflect a bank's financial performance and balance sheet integrity, by examining among others a copy of the latest report by the independent auditors (Le Bras and Andrews 2004). We therefore use a dummy variable to indicate whether the bank received a qualified or unqualified audit opinion.

Obviously, banks will be affected by the overall banking environment of the country in which they operate. Among others issues, Fitch considers the role and functions of: the banking supervisory authorities in the country in question, the degree of state control, the requirement for public reporting by banks and the accounting practices that lie behind the figures publicly reported by banks (Le Bras and Andrews 2004). In the present study to consider such issues, we use the Banking and Finance score estimated by the Heritage Foundation, that measures the relative openness of a country's banking and financial system. The score of this factor, may take the values of 1 (very low restrictions on banks), 2 (low restrictions on banks), 3 (moderate restrictions on banks), 4 (high restrictions on banks), or 5 (very high restrictions on banks). The score is estimated by determining: (a) whether foreign banks and financial services firms are able to operate freely, (b) how difficult it is to open domestic banks and other financial services firms, (c) how heavily regulated the financial system is, (d) the presence of state-owned banks, (e) whether the government influences the allocation of credit, and (f) whether banks are free to provide customers with insurance and invest in securities.

Another factor that Fitch takes into account is the strength and depth of bank's franchise as well as its ability to safeguard existing business and gain new ones. In the present study, the number of subsidiaries is included as a proxy for the diversification of business and franchise.

We finally employ two variables, the number of bank's shareholders and whether the bank is listed or not in a stock exchange, which are related to bank's corporate governance and ownership. According to Le Bras and Andrews (2004) the concentration of equity ownership might indicate that the majority shareholders have a strong vested interest in creating long-term value and closely monitoring management behavior. On the other hand, a potential concern in such cases is that the owners might rely heavily on extracting funds from the bank as source of income or to fund other business activities. Furthermore, if the bank is part of a broad holding company structure with multiple subsidiaries, unique issues may arise in order to access the decision-making process, lines of hierarchy and financial obligations and liabilities.

4 The MHDIS multicriteria decision aid

The problem considered in this case study falls within the multicriteria classification problematic that in general involves, the assignment of a finite set of alternatives $A = \{a_1, a_2, \dots, a_n\}$, each one described along a set of m criteria $g_1, g_2, \dots, g_m$, to a set of q ordered classes $C_1 \succ C_2 \succ \cdots \succ C_q$. In the present case study the alternatives involve the 215 observations, the criteria correspond to the ten financial and non-financial variables, and there are five ordered classes corresponding to the five rating scales.

The most common approach to address multicriteria classification problems is to develop a criteria aggregation model based on absolute judgments. The model provides a rule for the classification of the alternatives on the basis of their comparison to some reference profiles that distinguish the classes (cut-off points). In the present study, we use the MHDIS technique that has been found to perform well in similar problems in finance such as bankruptcy prediction (Gaganis et al. 2005), acquisitions prediction (Zopounidis and Doumpos 2002), and country risk (Doumpos and Zopounidis 2001).

Multi-group hierarchical discrimination distinguishes the groups progressively, starting by discriminating the first group from all the others, and then proceeds to the discrimination between the alternatives belonging into the other groups. To accomplish this task two additive utility functions are developed in each one of the $q - 1$ steps, where q is the number of groups. The first function $U_k(a)$ describes the alternatives of group C_1, while the second function $U_{\sim k}(a)$ describes the remaining alternatives that are classified in lower groups $C_{k+1}, \dots, C_q$.

$$U_k(a)=\sum_{i=1}^{m} p_{ki}u_{ki}(g_i) \quad \text{and} \quad U_{\sim k}(a)=\sum_{i=1}^{m} p_{\sim ki}u_{\sim ki}(g_i), \quad k=1,2,\ldots,q-1$$

The corresponding marginal utility functions for each criterion g_i are denoted as $u_{ki}(g_i)$ and $u_{\sim ki}(g_i)$ which are normalized between 0 and 1, while the criterion weights p_{ki} and $p_{\sim ki}$ sum up to 1. As mentioned above, the model is developed in $q-1$ steps. In the first step, the method develops a pair of additive utility functions $U_1(a)$ and $U_{\sim 1}(a)$ to discriminate between the alternatives of group C_1 and the alternatives of the other groups $C_2,\ldots,C_\text{q}$. On the basis of the above function forms the rule to decide upon the classification of any alternative has the following form:

If $U_1(a) \geq U_{\sim 1}(a)$ then a belongs in C_1
Else if $U_1(a) \leq U_{\sim 1}(a)$ then a belongs in $(C_2, C_3, \ldots, C_q)$

The alternatives that are found to belong into class C_1 (correctly or incorrectly) are excluded from further analysis. In the next step, another pair of utility functions $U_2(a)$ and $U_{\sim 2}(a)$ is developed to discriminate between the alternatives of group C_2 and the alternatives of the groups $C_3,\ldots,C_q$. Similarly to step 1, the alternatives that are found to belong in group C_2 are excluded from further analysis. This procedure is repeated up to the last stage $(q-1)$, where all groups have been considered. The overall hierarchical discrimination procedure is shown in Fig.1.

The estimation of the weights of the criteria in the utility functions as well as the marginal utility functions is accomplished through mathematical programming techniques. More specifically, at each stage of the hierarchical discrimination procedure, two linear programs and a mixed-integer one are solved to estimate optimally the two additive utility functions and minimize the classification error. Further details of the mathematical programming formulations used in MHDIS can be found in Zopounidis and Doumpos (2002).

5 Empirical results

Table 5 presents descriptive statistics for the final set of variables, while distinguishing between the five rating scales. As expected the performance of banks is in general better, in terms of all financial variables, for banks with higher ratings. The influence of the number of shareholders and subsidiaries is not clear. The number of banks listed on the stock exchange as a percentage of total banks from the same rating scale decreases as the rating decreases. As for the banking environment, banks rated above B/C in general operate in banking markets with low or very low restrictions, while those rated below D operate in markets with moderate to high restrictions.

Tables 6 and 7 present the results of the analysis regarding the significance (in weights) of the variables, in discriminating between observations from the five rating scales, and the classification accuracies of the MHDIS model respectively. To eliminate the problems due to the relatively small sample and ensure the proper development and validation of the model, we follow a tenfold cross-validation. That is, the total sample of 215 observations is initially randomly split into 10 mutually exclusive sub-samples (folds) of approximately equal size. Then ten models are

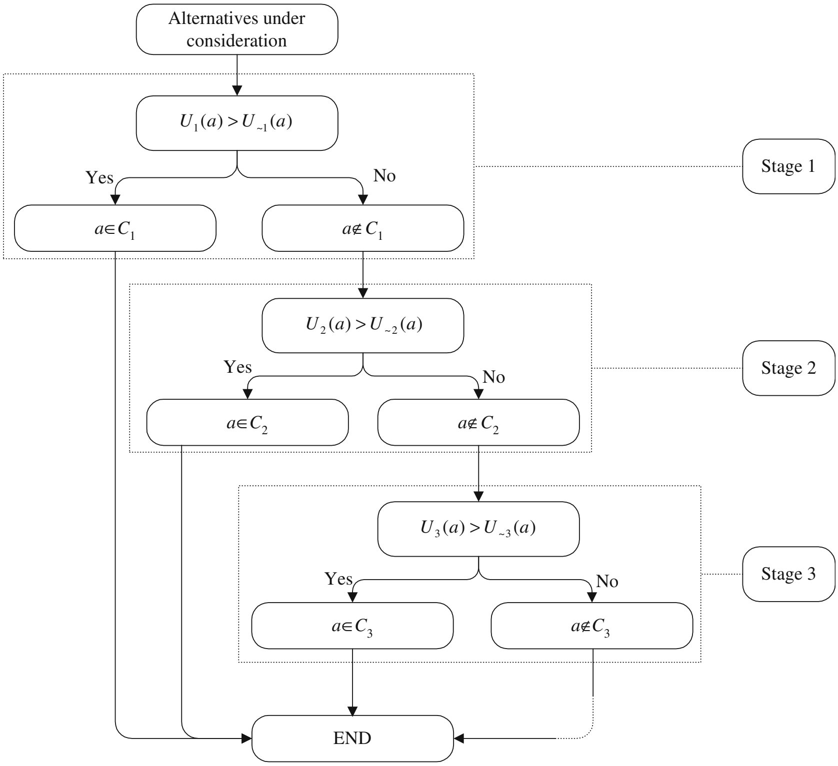

Fig. 1 The hierarchical procedure of M.H.D.I.S

developed, using each fold in turn for validation and the remainder for training. Thus, in each of the ten replications, the training sample consists of approximately 193 observations and the validation consists of 22 ones. The average error rate over all the ten folds is the cross-validated error rate.

The presented figures in Table 6 involve the average weights of the variables along all replications of the tenfold cross-validation. With five rating scales, the hierarchical discrimination process of MHDIS consists of four stages, during which eight additive utility functions are developed, in total. The utility function U_1 characterizes banks with ratings in the highest scale (i.e. A and A/B), whereas the utility function $U_{\sim 1}$ characterizes those assigned lower ratings (i.e. B and B/C, C and C/D, D and D/E, E). Similarly, the utility function U_2 characterizes banks assigned B and B/C ratings whereas $U_{\sim 2}$ characterizes the ones assigned lower ratings (i.e. C and C/D, D and D/E, E). The utility functions U_3 and $U_{\sim 3}$ characterize banks belonging in C and C/D scale and below C/D, respectively. Finally, U_4 characterizes banks assigned D and D/E ratings, while $U_{\sim 4}$ characterize banks assigned E ratings.

EQFUND, NIM and ROAE appear to be the most important financial variables (in terms of weights) in most cases. Hence, the results indicate that banks with higher levels of equity relatively to their customer and short term funding are assigned higher ratings. There are various reasons for which capital increases banks

Table 5 Descriptive Statistics for independent variables

	A and A/B	B and B/C	C and C/D	D and D/E	E
Panel A: continuous variables (mean values)					
EQFUND	8.28	10.38	8.15	5.46	4.39
NIM	2.23	2.49	2.56	2.47	1.61
ROAE	24.42	10.63	14.36	9.41	−2.75
LOANDEP	54.67	64.86	62.61	62.55	66.63
LIQDEP	33.90	26.78	24.51	22.59	17.96
OWNERS	2.50	8.10	5.29	7.40	4.03
SUBS	28.50	43.06	24.03	14.52	47.06
Panel B: categorical variables (No. of observations)					
AUDIT					
Qualified	0	0	1	4	2
Unqualified	4	22	48	57	12
N.A.	0	9	20	16	20
STEXCH					
Listed	2	25	54	57	21
Unlisted	2	6	15	20	13
BENV					
1 (Very low restrictions)	4	11	10	0	0
2 (low restrictions)	0	10	13	8	4
3 (moderate restrictions)	0	6	24	27	20
4 (high restrictions	0	4	22	42	10
5 (very high restrictions)	0	0	0	0	0

Notes: The financial bank-specific variables are defined in Table 3. OWNERS corresponds to the number of institutional shareholders, SUBS corresponds to the number of subsidiaries the banks owns, AUDIT is the auditors' opinion, STEXCH indicates whether the bank is listed in a stock exchange or not, BENV is the Heritage Banking and Finance Factor and shows the level of restrictions in the banking sector

Table 6 Variables weights in MHDIS model (averages over ten replications)

	$U_1(\%)$	$U_{\sim 1}(\%)$	$U_2(\%)$	$U_{\sim 2}(\%)$	$U_3(\%)$	$U_{\sim 3}(\%)$	$U_4(\%)$	$U_{\sim 4}(\%)$
EQFUND	17.88	7.09	13.90	12.58	16.26	19.10	17.67	13.85
NIM	6.50	8.54	10.73	11.53	9.73	13.01	38.35	33.06
ROAE	32.80	18.80	5.45	5.61	16.68	13.02	10.38	14.59
LOANDEP	4.19	7.66	8.56	6.98	6.77	8.01	7.61	10.34
LIQDEP	9.02	6.53	8.41	8.74	5.99	7.94	1.07	2.36
AUDIT	0.02	0.02	0.51	0.21	6.76	1.34	4.48	5.76
STEXCH	0.01	0.01	0.01	0.78	0.77	0.57	0.01	0.01
OWNERS	5.63	14.00	19.55	22.36	14.14	8.43	8.98	10.73
SUBS	11.11	22.60	17.20	16.28	11.28	16.94	9.71	8.87
BENV	12.83	14.75	15.68	14.92	11.61	11.65	1.74	0.42

Notes: The financial bank-specific variables are defined in Table 3. OWNERS corresponds to the number of institutional shareholders, SUBS corresponds to the number of subsidiaries the banks owns, AUDIT is the auditors' opinion, STEXCH indicates whether the bank is listed in a stock exchange or not, BENV is the Heritage Banking and Finance Factor and shows the level of restrictions in the banking sector

creditworthiness. First, capital serves as the last line of defense against insolvency risk, as any losses a bank suffers could be potentially written off against capital. Even in the case that insolvency becomes unavoidable, capital protects (to some degree) depositors, creditors and investors (Le Bras and Andrews 2004). Further-

Table 7 MHDIS classification results (average results over ten replications)

	A and A/B(%)	B and B/C(%)	C and C/D(%)	D and D/E(%)	E(%)
Training					
A and A/B	100.00	0.00	0.00	0.00	0.00
B and B/C	0.00	100.00	0.00	0.00	0.00
C and C/D	0.16	14.52	81.28	4.03	0.00
D and D/E	0.00	9.82	8.24	81.36	0.58
E	0.00	4.62	2.72	6.64	86.02
Average			89.73		
Validation					
A and A/B	75.00	0.00	25.00	0.00	0.00
B and B/C	3.33	76.67	11.67	5.00	3.33
C and C/D	2.00	20.16	62.49	13.01	2.34
D and D/E	0.00	16.87	14.98	55.30	12.85
E	0.00	7.36	19.26	12.69	60.69
Average			66.03		

more, capital allows the leveraging of a bank's growth and diversification, and a tight solvency position would be an obstacle to do so (Theodore 1999). Finally, as Rawcliffe and Andrews (2003) point out bigger banks (in terms of absolute size of a bank's equity) are more likely to be important to their domestic economics, increasing the probability to receive external support, if required, hence decreasing their risk of default.

Banks with higher return on equity and net interest margin, also receive higher ratings that is consistent with prior studies such as the ones of Poon et al. (1999) who find profitability to be positively related to higher ratings in the case of Moody's, and Wheelock and Wilson (2000) who reveal a statistically significant and negatively relation between profitability and probability of failure. NIM appears to be more important in characterizing banks that are assigned below D ratings, with weights that equal 38.35% and 33.06% in U_4, and $U_{\sim 4}$ accordingly, rather than banks with higher ratings. In contrast, ROAE is particular important in describing banks that receive a top rating (i.e., function U_1).

From the non-financial variables, OWNERS, SUBS and BEVN are the most important ones while the impact of AUDIT and STEXCH, is in most cases quite small. The importance of OWNERS might be attributed to the fact that a higher number of institutional shareholders implies that financial support will be more easily provided, and funds will be directed to the bank by its owners, if required. The empirical results of Konishi and Yasuda (2004) also indicate that the primary effect of the ownership by stable shareholders is to reduce total bank risk. SUBS indicates the importance of diversification and franchise value. First, banks with more subsidiaries are probably better diversified. Second, since owners have much to lose if the bank becomes insolvent, a bank with high franchise value may have an incentive to avoid risky business strategies (Konishi and Yasuda 2004).

Our results also indicate that lower restrictions in the banking sector result in higher ratings. This importance of BENV is consistent with recent studies on bank regulations that indicate a relationship between such regulations and banks' risk-taking incentives, performance, and banking crises[6] (e.g. Barth et al. 2001a, b, 2002, 2003a, b, 2004a; Demirguc-Kunt and Detragiache 2002; Konishi and Yasuda 2004; Gonzalez 2005; Fernandez and Gonzalez 2005). However, it should be mentioned that the impact of BENV is relatively small in the case of banks that receive low ratings. Unfortunately, BENV is an aggregate index that does not allow an interpretation of the impact of its individual components on credit ratings. In the discussion that follows we therefore attempt to offer some potential explanations while refereeing to some of these components and bank risk taking, on the basis of prior empirical evidence. For example, Barth et al. (2001a) find that greater regulatory restrictions on bank activities are associated with higher probability of suffering a major banking crisis, and lower banking sector efficiency. Barth et al. (2004a) also indicate that restricting bank activities is negatively associated with bank development and stability. Furthermore, while in the past concerns over the safety of existing banks made it difficult for a new bank to gain a license and enter the market, in recent years entry is encouraged and considered as a way to enhance competition with positive effects on efficiency, costs reduction and vulnerability of the banking sector to adverse shocks (Besanko and Thakor 1992; Cordella and Yeyathi 2002). Morgan and Strahan (2004) provide evidence of a positive association between foreign bank presence and economic volatility, while the results of Barth et al. (2004a) indicate that barriers to foreign-bank entry are positively associated with bank fragility. With respect to government ownership, Caprio and Martinez (2000) point out that it is significantly associated with increases in bank fragility, while Barth et al. (2001a) indicate that greater government ownership is associated with less efficient and less well developed financial systems. Finally, La Porta et al. (2002) find that countries with higher initial levels of government ownership tend to have less financial development and slower economic growth.

Table 7 shows that over the ten replications the MHDIS model can classify correct about 90% of firms on average. The lower accuracy rates are observed for the C and C/D scale that is not surprising since banks belonging to this scale are in an "intermediate" situation, and their correct identification is expected to be more difficult compared to banks belonging in other scales. These results indicate that in general, models developed with the considered variables are able to provide a satisfactory distinction between banks falling in the five scales, consistent with the ratings of Fitch. Nevertheless, since these results refer to the same observations that were used to develop the models, the potential upwards bias should be kept in mind and the classification results in the validation sub-sample are more appropriate for the proper evaluation of the model. Not surprisingly, the classification accuracies achieved in the validation set decrease in all cases, resulting in an average, among all scales, equal to 66.03%. However, it should be mentioned that the performance of MHDIS is quite robust, with classification accuracies in four out of the five scales above 60%. The highest classification accuracy is achieved for banks in rating scale B and B/C (76.67%) followed by A and A/B (75.00%), while on the opposite site the lowest accuracy is achieved for banks assigned D and D/E ratings (55.30%).

To extent the analysis on the suitability of MHDIS for the particular problem, a comparison is performed with discriminant analysis (DA) and ordered logistic regression (LR) that have been commonly used in the past for the development of credit risk models. The models generated through DA and LR are developed and tested following the same approach as for MHDIS. More detailed, using the same ten variables, the models are developed and tested through the tenfold

Table 8 Comparative classification results (average results over ten replications)

	A and A/B(%)	B and B/C(%)	C and C/D(%)	D and D/E(%)	E(%)	Average(%)
Training						
MHDIS	100.00	100.00	81.28	81.36	86.02	89.73
DA	100.00	43.41	37.75	59.48	70.92	62.31
LR	0.00	59.08	49.08	75.67	33.68	43.50
Validation						
MHDIS	75.00	76.67	62.49	55.30	60.69	66.03
DA	75.00	50.00	34.47	56.61	52.57	53.73
LR	0.00	58.33	45.42	75.53	29.52	47.55

cross-validation approach described above. The classification accuracies of all methods are summarized in Table 8. The results highlight the efficiency of the MHDIS multicriteria approach compared to both DA and LR, in terms of its overall accuracy.

With regard to the training sample, the overall classification accuracy of MHDIS (89.73%) is significantly higher than that of both DA (62.31%) and LR (43.50%) that is not surprising since MHDIS outperforms the other methods in all rating scales. Similarly to MHDIS, DA experiences a decrease in its classification accuracy in the validation sample. In contrast, LR experiences a small increase. Hence, MHDIS still performs better than both DA and LR although the differences among the three methods are lower than in the training sample. In terms of individual classification accuracies in the validation sample, MHDIS achieves a relatively lower accuracy than DA only in the case of D and D/E scale and same on the case of A and A/B scale, but it clearly outperforms DA in the remaining three scales. LR performs better than MHDIS in the case of D and D/E scale but is inferior in all other cases.

6 Concluding remarks

Since the release of the first proposal for the new capital framework in 1999 and especially after the release of its final form on 2004 the credit ratings industry has received increased attention. In the present study we examined, and to some extent replicated the Fitch individual bank ratings on Asian banks, using the MHDIS multicriteria decision aid approach. Five financial and five non-financial variables covering several bank characteristics, as well as the banking sector of the country that the bank operates, were included in the model that was developed and tested through a tenfold cross-validation.

Equity/customer and short term funding, net interest margin and return on average equity appeared to be the most important financial variables, while the number of shareholders, the number of subsidiaries and the banking environment of the country in which the banks operate are the most important non-financial ones. In terms of classification accuracies, the results showed that the model developed through MHDIS can replicate the credit ratings of Fitch with a satisfactory accuracy and outperform discriminant analysis and ordered logistic regression that were used for comparison purposes. Thus, MHDIS provides an attractive and promising framework for complex decision problems such as credit rating were many groups are involved.

Future research could be directed towards numerous directions. First, a comparison with alternative methods could reveal more information for the efficiency of MHDIS. A second possible extension would be the combination of the individual models into an integrated one; an approach that has yielded promising results in previous studies. Third, it would be interest to re-estimate the model using additional financial and non-financial variable that were not available in our case, such as measures of asset quality, executive and director remuneration, and the independence and effectiveness of the board of directors. Fourth, it would be interesting to extent the study towards other regions (e.g. Europe, U.S., Latin America) and examine whether there are differences in the characteristics and market conditions that affect the ratings.

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