Are Bank Ratings Coherent with Bank Default Probabilities in Emerging Market Economies ?

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Abstract

In this paper we investigate the coherence between bank ratings and default probability in emerging market economies using scoring and mapping techniques. In order to achieve its disciplining role, the rating should be coherent with the default risk it summarizes and disseminate. This issue is particularly crucial in emerging economies where under-developed financial markets, banking sector accrued opacity, and inadequate regulatory, institutional and legal environment affect banker's risk taking behavior and bank's default risk. Scoring results show a correct quantification of agency rating grades and thus their coherence. Mapping results show a tendency of the rating to aggregate bank's default risk information into intermediate low category grades.

Key words : emerging market economies, default probability, bank rating, scoring and mapping methods.

JEL classification : C35, F39, G21.

1 Introduction

Ratings are considered as an important indicator of issuer's default risk by many economic agents, like regulators and investors. A strong consensus exists, considering ratings as a crucial vector of information, superior to the information available on the financial markets (see for example Hand et al. 1992, Reitert and Zeibert 1991 and Ederington et al. 1987).

In the Third Pillar of the Basel II Reform framework, an important role is provided to agency ratings. They give a signal on counterparty's default probability to other market participants and economic agents. This type of information should contribute to the efficiency of market discipline. It is especially important in emerging market economies, where under-developed financial markets, banking sector accrued opacity, and inadequate regulatory, institutional and legal environment may create adverse incentives to take excessive risks by banks and therefore increase their default probability (Rojas-Suarez 2000, Rojas-Suarez 2001). An efficient market discipline is needed in order to counterbalance such incentives.

The coherence of the agency rating with the default probability is then crucial within such framework, because it can foster incentives to adopt a conservative risk taking behavior in banks. If the rating is coherent with the default risk which it summarizes in a notation, it gives a viable signal about bank strength, and may therefore enhance the market's transparency and fosters market discipline. Thus, the bank is incited to adopt a conservative risk taking behavior because excess risk impacts positively its default probability, inducing a rating downgrade, and a negative signal to the market and the regulator. The agency rating can also be used as a supervisory tool, giving the regulator an additional signal about bank fragility. Using such signal improves the assessment of on-site examination and regulatory actions against unhealthy banks, in order to build a regulatory discipline, which should also affect excess risk taking incentives in banks.

An important literature deals with issues such as rating and rating prediction models (see Beaver 1966, Pinches and Mingo 1975, Kaplan and Urwitz 1979, Fons and Kimball 1991), as well as Ederington et al. (1987), and

Brister et al. (1994), as well as comparative studies of different agency ratings (see Cantor and Packer 1995, Cantor and Packer 1996, Jewell and Livingston 1999, Shin and Moore 2003). Few studies deal with the coherence of ratings with bank's default probabilities in emerging market economies[1].

Therefore, the aim of this article is to investigate the coherence between Moody's ratings and the default probabilities from a simple scoring model applied to banks from emerging market economies. The scoring and mapping methodology of Carey and Hrycay (2001) is adopted. Further investigation into bank rating determinants is also presented.

The article is organized as follows. A brief description of bank's default and rating systems is proposed in section 2. Section 3 describes the methodology and the data used in the study. The results are discussed in section 4. Finally, section 5 concludes.

2 Bank's default and rating systems in emerging market economies

The interest for bank failures comes mainly from its costs : financial losses for the stakeholders (shareholders, clients, deposits insurance fund), loss of competition, and a potential destabilization of the financial system, through contagion mechanisms, several individual failures leading to a banking crisis. The resolution of these failures is a waste of resources, particularly scarce in emerging market economies (EME) (Honohan 1997)[2].

An important literature deals with the explanation and prediction of bank's default, using econometric models which usually follow a CAMEL typology for selecting proxies of risk factors influencing bank's default risk (see Demirgüç-Kunt 1989). Agency rating can be understood as a signal summarizing information about bank's default probability. One of the aim

[1]Except Krämer and Güttler (2003) and Güttler (2004), who compare the rating's default prediction accuracy using notations from S&P and Moody's for samples with all type of issuer and geographic area.

[2]For example, the banking crisis in Indonesia (1997) and Thailand (1997-98) costed about 50-55% and 42.3% of the GDP respectively in term of restructurization (fiscal contribution).

of a rating is to disseminate information about the issuer's capacity to reimburse its debt. Therefore, the rating gives a synthetic indicator of default risk of this issuer.

Following Crouhy et al. (2001), a rating system is based on quantitative and qualitative evaluation of default risk. The final decision concerning the rating is done on general considerations, as well as subjective judgment of the analyst. Financial documents, management quality, competition, macroeconomic and sector fundamentals contribute to the rating process. These ratings correspond to a classification of the issuers or issues in grades which reflect expected losses.

Following Ferri et al. (1999), the rating agencies play an important role in financial markets, through the production of information and its dissemination to market participants. This is supposed to enhance market discipline. The rating grade is a crucial determinant of the issue's interest rate as well as the number of potential investors.

In emerging market economies, the rating is even more important because of less developed financial markets, usually more opaque, with a weak market discipline. This under-development of financial markets, an opaque banking sector, and an inadequate regulatory, institutional and legal environment are some of the emerging markets' specific features which may give the rating a crucial role in investor's but also regulator's decision making. The weight given to the rating in an investor's decision is even greater. In such a framework, the rating plays a "guiding" role. Concerning banking industry, the rating's availability gives a better transparency of bank's health. Banks play a crucial role in the economic development process in emerging countries. In such framework, the rating may foster market discipline through viable and precise information's dissemination, influencing bank's risk taking behavior. The rating can also be useful for supervisory purposes, enhancing regulatory discipline, and also affecting bank's risk taking. Therefore, the role of the rating as a vector of information in these countries shouldn't be underestimated, and their coherence with default risk should be investigated.

Moody's Investors Service has launched in 1995 a new type of bank's rating : the Moody's Bank Financial Strength Rating (MBFSR). MBFSR

corresponds to Moody's opinion on the internal financial strength of a bank. The determinants of this new rating are different from traditional ratings (like debt, credit, bank deposits, syndicate loans ratings, ...). MBFSR is available for banks from 50 countries. The grades range from A (best rating) to E (worst rating). MBFSR is the outcome of a financial analysis and a subjective judgment of the analyst. It is available on a solicited and unsolicited basis. Poon et al. (1999) have studied the MBFSR determinants. Their results show that this rating doesn't have a high supplementary informational contribution, when compared to other Moody's traditional ratings. The MBFSR can be understood as a synthetic indicator of bank's default probability, as it aims at summarizing information about bank's financial strength.

The Fitch IBCA, Duff & Phelps agency is specialized in banks' rating, via its company - Fitch Ratings. It produces only solicited ratings, contrary to Moody's. The Fitch Individual Rating (FIR) evaluates the bank's risk exposure, risk appetite and risk management capabilities. It ranges from A (best rating) to E (worst rating). It represents Fitch's opinion on the probability that the bank would require external support. Factors like profitability, accounting integrity, charter value, management's quality, operating environment, ... are taken into account during the rating process.

3 Methodology and data

3.1 Methodology

We adopt the scoring and mapping methodology from Carey and Hrycay (2001). We apply a logit model to estimate default probabilities. Then, we use their distribution to build simulated rating grades, and confront them to agency rating grades and their historical default probabilities. The estimation of the default probability allows to quantify the ratings grades (both the simulated and the agency ones) and to evaluate their coherence. The mapping of the simulated ratings into the agency ratings allows to deepen the ratings coherence investigation. Through this method we can also test

the possibility of using such approach for building internal rating systems to manage interbank risk exposure.

This methodology allows to formally link "real" default probabilities, predicted default probabilities and the quantified default probabilities.

We suppose that each issuer i is characterized at time t by its distance to default D_{it} and the volatility of this distance V_{it}. In t, the (unobserved) default probability at a time horizon of n years, noted P_{nit}, is the probability that D_{it} falls to 0 during the time interval $[t, t+n]$.

The aim of a rating system is to measure the default risk at a time horizon of n years through the aggregation of information about D and V into an estimation of the default probability $P^r_{nit} = f(D_{it}, V_{it})$. The rating gives a scale which specifies the grade G_{nit} associated to each value of P^r_{nit}. Under the hypothesis that P^r_{nit} measures P_{nit}, each issuer in the same grade have P_{nit} which values are within the interval of default probabilities determining the rating grade. The rating process involves subjective human judgement. Therefore, P^r_{nit} is a latent variable. The quantification of the mean default probability by rating grade involves the estimation of individual default probabilities P^q_{nit}.

The quantification of the rating grade can be obtained using scoring models. The mapping methods use the median issuer or the mean weighted default rate. These methods decompose into two steps. First, it equalizes each internal rating grade to an external rating grade. Second, it uses the mean default rate corresponding to the median external rating grade as an estimator of the mean default probability of the internal rating grade[3].

In this article, we apply this methodology in order to investigate the coherence of agency bank's ratings (Moody's Bank Financial Strength Rating MBFSR and Fitch Individual Rating FIR) with bank's default risk.

To summarize, we proceed in 4 steps :

1. we apply a logit model as the scoring model in order to estimate individual default probabilities. The scoring function is defined as a logit

[3]The subjective mapping (through human judgment) is quite difficult to apply, as internal rating systems are defined on often subjective criteria. The mechanical mapping is a solution, but has its own problems, especially selection bias (see Carey and Hrycay 2001).

model :

$$\log\left(\frac{p\,(DEFAULT)}{1-p\,(DEFAULT)}\right)=\alpha+Y_i'\beta+\varepsilon_i,$$

with $p\,(DEFAULT)=\frac{\exp^W}{1+\exp^W}$, $W=\alpha+Y_i'\beta+\varepsilon_i$, Y_i' = risk factors, the residuals ε_i having a logistic distribution[4], noted $\hat{p}_D$,

2. using the distribution of the default probabilities $\hat{p}_D$, we build simulated rating systems, following Moody's reports (Hamilton et al. 2004), in order to obtain an ordinal scale of rating grades corresponding to different default risks,

3. we calculate the following descriptive statistics : means and medians of estimated probabilities $\hat{p}_D$, as well as observed default rate frequencies, by simulated and agency (Moody's and Fitch) rating grades,

4. we confront the simulated rating grades to agency rating grades in order to proceed to the mapping, using historical default rates of Moody's and Fitch ratings.

3.2 Data

We use data extracted from the Bankscope (2003) database, containing accounting data on banks from emerging market economies for the period from 1998 to 2002, including default banks[5], and the Moody's (Bank Financial Strength Ratings) and Fitch (Fitch Individual Ratings) ratings. After having bound and cleaned the data, we obtain two samples of 483 and 257 banks for Moody's and Fitch respectively, covering emerging market economies from

[4]See Maddala (1983) for a detailed description of logit models.

[5]A default banks database has been build for emerging market countries from the three areas of South-East Asia, South America and Central and Eastern Europe. In order to get information about default banks, we have contacted local regulatory and supervisory institutions. We have also used information from the on-line database Banker's Almanac. The database allows to identify the name of the default bank and the time of default. A bank is considered as default when it's under one of the following procedure : external administration (regulatory and restructuring agency support), banking licence suspension or revocation, liquidation, failure.

South-East Asia, South America and Central and Eastern Europe (CEE). 68 and 48 defaults are present in both samples[6].

The definitions of the Moody's and Fitch ratings are given in the tables hereafter.

Table 1: Definition and frequencies of the Moody's Bank Financial Strength Rating

MBFSR	Observations	Definition
A	0	Exceptional intrinsic financial strength. Major institutions with highly valuable franchise value, strong financial fundamentals, and a very attractive and stable operating environment.
B	12	Strong intrinsic financial strength. Important institutions, with valuable franchise value, sound financial fundamentals and stable operating environment.
C	57	Good intrinsic financial strength. Valuable franchise value, acceptable financial fundamentals within a stable operating environment, or above average financial fundamentals within an unstable operating environment.
D	237	Weak intrinsic financial strength. Weak franchise value, financial fundamentals and an unstable operating environment.
E	177	Very weak intrinsic financial strength. Periodical external support is necessary. Doubtful franchise value, deficient financial fundamentals, and a highly unstable operating environment.

Source : Moody's Investors Service, Global Credit Research, and Poon et al. (1999).

We use the logit model as a scoring model to estimate default probabilities, which distribution serves as a support for building the simulated rating scale. The logistic function is particularly suitable in this framework, as the estimated probabilities are within the $[0, 1]$ interval.

[6]See table 15 and 16 in appendix for the countries in our 2 samples.

Table 2: Definition and frequencies of the Fitch Individual Rating

FIR	Frequency	Definition
A	4	Very strong bank. Characterized by excellent profitability, accounting integrity, charter value, management quality, operating environment, and perspectives.
B	37	Strong bank, without major problems. Characterized by a good profitability and accounting integrity, an important charter value, sound management, and a stable operating environment and good perspectives.
C	84	Adequate bank, with problems concerning profitability and accounting integrity, charter value, management quality, operating environment or perspectives.
D	101	Bank having internal and/or external fragilities. Profitability, accounting integrity, charter value, management, operating environment or perspectives are problematic.
E	31	Bank having serious problems, implying external support.

Source : Fitch IBCA, Duff & Phelps, FitchRatings.

We use this distribution to build a rating grades scale, as shown in table 3.

We also build a simulated rating containing 4 grades for the MBFSR, as we don't have any A MBFSR in our sample[7]. We aggregate the first two grades from the scale 5 simulated rating system, in order to obtain a 4 rating grades scale, as shown in table 4.

[7]Poon et al. (1999) has only 4% of A's in their sample, as this rating grade is given only to bank with exceptional internal financial strength. Such strength is hardly found in banks from emerging market economies.

Table 3: Five grades simulated rating system

$\hat{p}_D$	simulated grade (scale 5)
< 0.001	1
$[0.001, 0.0025[$	2
$[0.0025, 0.01[$	3
$[0.01, 0.05[$	4
≥ 0.05	5

Table 4: Four grades simulated rating system

$\hat{p}_D$	simulated grade (scale 4)
< 0.0025	1
$[0.0025, 0.01[$	2
$[0.01, 0.05[$	3
≥ 0.05	4

4 Results and discussion

Our aim is not to build the most performant default model, that is why we use a logit model containing 6 explanatory variables, proxies of the principal risk factors found in the literature (see Demirgüç-Kunt 1989), which have significant impact on bank default probability. These factors follow a CAMEL typology, with the dimensions of capital adequacy with respect to the loan portfolio (EQTL = Equity / Total Loans), bank management (PXTOX = Personal Expenses / Total Operating Expenses), profitability (NIM = Net Interest Margin), liquidity (LIQATA = Liquid Assets / Total Assets and TDTA = Total Deposits / Total Assets), and portfolio quality (LLRNPL = Loan Loss Reserves / Non Performing Loans).

In the two following subsections, we first show the results for the MBFSR sample in subsection 4.1, then for the FIR sample in subsection 4.2.

Table 5: Bank default logit model results - MBFSR sample

	coef.	s.e.
INTERCEPT	8.981^{***}	1.71
EQTL	-0.136^{***}	0.04
PXTOX	-0.004	0.017
NIM	-0.261^{*}	0.136
LIQATA	-0.046^{**}	0.023
TDTA	-0.076^{***}	0.017
LLRNPL	-0.023^{***}	0.006
Ndef.	68	
N	483	
LR	185.11^{***}	
LogL	-103.73	
R^2 Mc Fadden	47.15	
Hosmer & Lemeshow	179.26^{***}	
Def. reclas. rate	86.8	

coef. : estimated coefficient, s.e. : standard-error.

***, ** and * : significant coef. at 1%, 5% and 10%.

Ndef.: number of defaults, N : number of banks.

LogL : logarithm of the likelihood.

LR : likelihood ratio.

Def. reclas. rate : default reclassification rate.

4.1 Moody's Bank Financial Strength Rating results

We present in table 5 the results of the bank default logit model for the MBFSR sample.

The significant coefficients have expected signs for the variables : EQTL, NIM, LIQATA, TDTA and LLRNPL. A better capital adequacy, a good interest margin, more deposits and liquid assets and a better cover of NPL with reserves reduce bank default probability. The statistics of the model are satisfactory (significant LR, good adjustment quality and a good default reclassification rate, above 85%).

We use the distribution of the estimated bank default probabilities to

build the simulated rating system, by dividing the interval in 5 and 4 grades[8]. The division in 5 rating grades serves as a benchmark, the division in 4 rating grades is done due to data availability, as we have only 4 MBFSR grades in our sample : B, C, D et E. Using the mean and median estimated default probabilities, we can quantify each simulated rating grade, and compare them to the observed default rate by simulated grade.

In what follows, we use the following abbreviations : med. - median, low. and up. CI lim. - respectively lower and upper confidence interval limits at the 95% level, def. rate - observed default rate, and N def. - number of defaults. We note the estimated default probability as $\hat{p}_D$. The mean and median values of $\hat{p}_D$ are obtained using the bank default logit model. The values of def. rate are the proportion of defaults in the sample of the banks by each grade. Finally, the lower and upper CI. limits at the 95% are for the observed default rate, by grade. The results are shown in table 6.

Table 6: Means and medians of the estimated default probability and default rate by simulated rating grade - MBFSR sample

scale (5)	mean $\hat{p}_D$	med. $\hat{p}_D$	def. rate	N def.	low. CI. lim.	up. CI. lim.
1	0.000155	0.000036	0	0	0.0000	0.0000
2	0.001692	0.001625	0	0	0.0000	0.0000
3	0.005957	0.005837	0.0549	5	0.0081	0.1018
4	0.02583	0.02437	0.011	1	0.0000	0.0324
5	0.376008	0.359755	0.3584	62	0.2869	0.4298
scale (4)	mean $\hat{p}_D$	med. $\hat{p}_D$	def. rate	N def.	low. CI. lim.	up. CI. lim.
1	0.000454	0.00007	0	0	0.0000	0.0000
2	0.005957	0.005837	0.0549	5	0.0081	0.1018
3	0.02583	0.02437	0.011	1	0.0000	0.0324
4	0.376008	0.359755	0.3584	62	0.2869	0.4298

These first results show that, for the scale 5, the mean estimated default

[8]The number of observations by simulated rating grades are (decreasing with the rating) : 103, 25, 91, 91, 173 for the scale 5 rating grades and 128, 91, 91, 173 for the scale 4 rating grades.

probability under-estimates the observed default rate, except for grade 5 - the most risky. The means and medians of the estimated default probability are close for every grade, except grade 1. As the number of default are null for the low risk grades 1 and 2, there are important differences between the estimated default probability and observed default rate. For each grade, the mean of the estimated default probability is within the limits of the CI at the 95% level, except for grade 3.

The conclusions are similar for the scale 4, despite the fact of aggregating the lowest risk grades, which reduces the number of grades without observed defaults. The mean estimated default probability is close to the observed default rate only for the last grade 4 - the most risky. The means and medians of the estimated default probability are also close. Finally, for each grade, the mean $\hat{p}_D$ is within the CI limits at the 95% level, except for grade 3.

We show the same descriptive statistics (mean and median estimated default probability, observed default rate and CI limits at the 95% level) by MBFSR grade in table 7.

Table 7: Means and medians of the estimated default probability and default rate by MBFSR grade

MBFSR (4)	mean $\hat{p}_D$	med. $\hat{p}_D$	def. rate	N def.	low. CI. lim.	up. CI. lim.
B	0.013101	0.011086	0	0	0.0000	0.0000
C	0.033047	0.003466	0.0351	2	0.0000	0.0829
D	0.07714	0.007155	0.0844	20	0.049	0.1198
E	0.269362	0.14728	0.2599	46	0.1953	0.3245

It is important to notice that the rating is by nature through the cycle, but the logit model estimates a point in time default probability. If the default model can correctly estimate individual default probabilities at a horizon of one year, it should also allow to estimate correctly mean default probability by MBFSR grade[9].

[9]Of course, the discriminatory power of the logit model is imperfect.

The results in table 7 show that the mean estimated default probabilities are close to the observed default rates for the riskiest grades - C, D and E. For grade B, the model over-estimates the effective default risk, as no default is observed for this grade in our sample. The means and medians of the estimated default probability are far away one from another, except for grade B. The mean estimated default probabilities are within the CI limits at the 95% level for each grade.

Finally, we use the default probability (one year transition to the default grade) of the Moody's rating grades in order to map the simulated rating system into the agency rating system. The results are shown in table 8. New abbreviations are the following : hist. def. rate - historical default rate, and mean weigth. hist. $\hat{p}_D$ - mean weighted historical estimated default probability. Historical default rates correspond to the historical transition rates to the DEFAULT category of bank's ratings at one year horizon during the period 1970-2002 for the emerging market economies[10]. The weighted mean estimated default probability is calculated as follows :

$$mean\,weigth.\,hist.\,\hat{p}_D = \frac{N_g \cdot def.\,hist.\,rate}{N},$$

N_g being the number of observations by each simulated grade, and N the total number of observations in the sample.

Following the results shown in table 8 for the scale 5, the first 4 simulated grades correspond to a median D Moody's rating, which "aggregate" default information of the 4 simulated grades into an intermediary low category agency rating[11]. The last simulated grade 5 corresponds to a median E Moody's rating. The corresponding historical default rates underestimate the default risk compared to observed default frequencies. The mean weighted historical $\hat{p}_D$ under-estimate even more the observed default rates. The conclusions are similar for scale 4. Thus, the use of this map-

[10]We use the transition matrix including withdrawn ratings, supposing the following relationship between the Moody's credit ratings and MBFSR (the speculative grade begins at the Baa rating for Moody's) : Aaa = A, Aa = B, A = C, Baa-B=D, Caa-C = E. Source : Credit Risk Calculator, Moody's Investor Services.

[11]The importance of this category in our sample could play a role in this result.

Table 8: Mapping of the simulated ratings into Moody's ratings

scale (5)	med. MBFSR	hist. def. rate	mean MBFSR	mean weight. hist. $\hat{p}_D$	def. rate	low. CI lim.	up. CI lim
1	D	0.025	2.98	0.005331	0	0.0000	0.0000
2	D	0.025	3.04	0.001234	0	0.0000	0.0000
3	D	0.025	3.02	0.00471	0.0549	0.0081	0.1018
4	D	0.025	2.86	0.00471	0.011	0.0000	0.0324
5	E	0.125	3.62	0.044772	0.3584	0.2869	0.4298
scale (4)	med. MBFSR	hist. def. rate	mean MBFSR	mean weight. hist. $\hat{p}_D$	def. rate	low. CI lim.	up. CI lim
1	D	0.025	2.99	0.00629	0	0.0000	0.0000
2	D	0.025	3.02	0.00471	0.0549	0.0081	0.1018
3	D	0.025	2.86	0.00471	0.011	0.0000	0.0324
4	E	0.125	3.62	0.044772	0.3584	0.2869	0.4298

ping method would aggregate the default information into intermediate low category agency rating[12].

4.2 Fitch Individual Rating results

We present the results of the bank default logit model for the FIR sample in table 9.

Following these results, most of the significant coefficients have expected signs (EQTL, TDTA et LLRNPL). The model's statistics are satisfactory (significant LR and good adjustment quality), as well as a satisfactory default reclassification rate, above 85%.

Using the distribution of the estimated default probability, we build a simulated rating system, following the same rules as exposed in section 3. Then, we proceed following the same 4 steps as for the MBFSR in subsection 4.1. The same abbreviations apply.

[12] An alternative division of the distribution of estimated default probabilities could alter these results.

Table 9: Bank default logit model results - FIR sample

	coef.	s.e.
INTERCEPT	10.925^{***}	2.845
EQTL	-0.338^{***}	0.076
PXTOX	0.02	0.025
NIM	0.013	0.17
LIQATA	0.009	0.029
TDTA	-0.108^{***}	0.03
LLRNPL	-0.029^{***}	0.01
Ndef.	48	
N	257	
LR	122.65^{***}	
LogL	-62.42	
R^2 Mc Fadden	49.56	
Hosmer & Lemeshow	529.34^{***}	
Def. reclas. rate	87.5	

coef. : estimated coefficient, s.e. : standard-error.

*** : significant coef. at 1%.

Ndef.: number of defaults, N : number of banks.

LogL : logarithm of the likelihood.

LR : likelihood ratio.

Def. reclas. rate : default reclassification rate.

Following these results[13], the mean estimated default probabilities by simulated grade over-estimates the observed default rate, as we don't have any defaults for the best grades 1 and 2, and under-estimates the observed default rate for the grade 3. The means and medians of the estimated default probabilities are close. Only the mean estimated default probabilities for grade 3 and 5 are within the CI limits of the 95% level.

We observe a homogeneity in the observed default rate's repartition by rating grades, with a number of observed default lower for the E grade compared to the D grade. The mean estimated default probability are close to the observed default rate, with an over-estimation for the A and D grades,

[13]The repartition of the banks per simulated grades is the following (decreasing with the rating) : 44, 12, 36, 53, 112.

Table 10: Means and medians of the estimated default probability and default rate by simulated rating grade - FIR sample

scale (5)	mean $\hat{p}_D$	med. $\hat{p}_D$	def. rate	N def.	low. CI. lim.	up. CI. lim.
1	0.000135	0.000035	0	0	0.0000	0.0000
2	0.001038	0.001554	0	0	0.0000	0.0000
3	0.005629	0.00563	0.0833	3	0.0000	0.1736
4	0.026473	0.024097	0	0	0.0000	0.0000
5	0.411889	0.434058	0.4018	45	0.311	0.4926

Table 11: Means and medians of the estimated default probability and default rate by FIR grade

FIR (5)	mean $\hat{p}_D$	med. $\hat{p}_D$	def. rate	N def.	low. CI. lim.	up. CI.
A	0.013005	0.012224	0	0	0.0000	0.0000
B	0.027761	0.00715	0.0541	2	0.0000	0.1269
C	0.114728	0.004343	0.1548	13	0.0774	0.2321
D	0.245638	0.134073	0.2079	21	0.1288	0.2871
E	0.394766	0.444863	0.3871	12	0.2156	0.5586

and an under-estimation for the B grade. Except for the extreme risk grades - A and E - the means and medians of the estimated default probabilities are far away one from another. The mean estimated default probability are within the CI limits at the 95% level.

The results of the mapping [14] are satisfactory for the first 2 grades of the simulated rating (the less risky). For the 3 other grades, the mapping results are highly unsatisfactory, as the corresponding historical default rates under-estimate the observed default rates.

[14] We apply the following correspondence between the FIR and the Fitch credit ratings, using the transition matrix to the category DEFAULT at one year horizon, for the period 1990-2002 : AAA=A, AA=B, A=C, BBB-B=D, CCC-C=E. Source : FitchRatings.

Table 12: Mapping of the simulated ratings into Fitch ratings

scale (5)	med. FIR	hist. def. rate	mean FIR	mean weight. hist. $\hat{p}_D$	def. rate	low. CI lim.	up. CI lim
1	B	0.0000	3	0.000086	0	0.0000	0.0000
2	B/C	0.0005[a]	2.83	0.000023	0	0.0000	0.0000
3	C	0.0005	3.06	0.00007	0.0833	0.0000	0.1736
4	C	0.0005	3.17	0.000103	0	0.0000	0.0000
5	D	0.0529	3.97	0.023054	0.4018	0.311	0.4926

[a] : The median Fitch rating being equal to 2.5, we use the historical default rate corresponding to the rating C.

4.3 Further investigations into the ratings determinants

In order to deepen our inquiry, we investigate the determinants of the Moody's and Fitch ratings. In a first step, we introduce the same variables used in the scoring model in a bank's rating ordered logit model. This allows us to check if these variables are still significant and keep the same signs. It also allows us to test if they can discriminate correctly between the different ratings grades, by checking the significancy of the intercepts in the ordered logit.

The results are shown in tables 13 and 14 for the MBFSR and FIR respectively[15].

We first comment the results for the MBFSR. Compared to the scoring model (see table 5), the variable EQTL is no more significant, whereas the variable TDTA is significant with a positive sign. The capital adequacy dimension seems to not have any influence on the Moody's rating, but the deposits to assets ratio have a positive impact on the cumulative probability of having an E rating. Thus, the moral hazard hypothesis seems to be validated in the MBFSR framework - the more a bank is risky and fragile on the assets' side, the more it requires deposits to fund herself (deposits being

[15]Recall that in the ordered logit framework we model the cumulative probability of having the worst rating class - p(MBFSR=4) and p(FIR=5) respectively - corresponding to the rating class E in both cases, for traceability with the default model.

Table 13: MBFSR ordered logit results

	coef.	s.e.
INTERCEPT 4	0.718	0.575
INTERCEPT 3	3.564***	0.597
INTERCEPT 2	5.575***	0.665
EQTL	0.004	0.005
PXTOX	−0.026***	0.007
NIM	−0.058***	0.017
LIQATA	−0.027***	0.008
TDTA	0.031**	0.006
LLRNPL	−0.005***	0.001
N	483	
LR	120.64***	
LogL	−452.25	
R^2 Mc Fadden	11.77	
Cor. reclas. rate	73.6	

coef. : estimated coefficient, s.e. : standard error.

*** and **: significant coef. at the 1% and 5% level.

N : number of banks.

LogL : logarithm of the likelihood.

LR : likelihood ratio.

Cor. reclas. rate : correct reclassification rate.

one of the cheapest source of funds).

All of the intercepts are significant, except INTERCEPT 4. It corresponds to the MBFSR E grade - the worst quality rating. It seems that the variables from the scoring model cannot correctly discriminate the Moody's rating grades, particularly the one corresponding to the least financially strong bank[16].

The evidence is similar for the FIR ordered logit results. All variables are significant as in the scoring model (with the same signs, see table 9), except for TDTA. All the intercepts are significant, except INTERCEPT

[16]Notice that when we aggregate the MBFSR E and D classes, the ordered logit results show that all intercepts are significant. Therefore, the same risk factors used in the scoring model are capable to discriminate correctly no more than 3 financial strength rating grades in our sample.

Table 14: FIR ordered logit results

	coef.	s.e.
INTERCEPT 5	−1.198	0.889
INTERCEPT 4	1.181	0.892
INTERCEPT 3	3.193***	0.903
INTERCEPT 2	5.986***	1.062
EQTL	−0.015*	0.008
PXTOX	−0.017*	0.01
NIM	0.032	0.027
LIQATA	−0.018	0.011
TDTA	0.008	0.009
LLRNPL	−0.008***	0.01
N	257	
LR	71.92***	
LogL	−306.24	
R^2 Mc Fadden	10.51	
Cor. reclas. rate	74.9	

coef. : estimated coefficient, s.e. : standard error.

*** and **: significant coef. at the 1% and 5% level.

N : number of banks.

LogL : logarithm of the likelihood.

LR : likelihood ratio.

Cor. reclas. rate : correct reclassification rate.

5 and INTERCEPT 4, corresponding to the worst rating grades E and D. Again, using the same risk factors as in the scoring model doesn't allow to correctly discriminate between the FIR grades, especially the worst ones[17].

Following these results, other factors should be included in the rating's model in order to discriminate precisely each rating grade, especially the worst. These results also indicate that the coherence between the rating and the default probability could be affected by the risk factors used in the scoring model. Adding new variables (regulatory and institutional factors, macroeconomic and market structure factors, ...) might allow us to investigate this

[17]Notice also in this case that when we aggregate the FIR E and D grades, all the intercepts are significant in the ordered logit regression.

issue more deeply[18].

5 Conclusion

This paper proposes an investigation of the coherence between agency rating - Moody's Bank Financial Strength Rating and Fitch Individual Rating - with the results of a bank default logit model in emerging market economies. In order to achieve this goal, we apply a scoring and mapping methodology, following Carey and Hrycay (2001), to a sample of rated banks from emerging market economies. The results show that by using a simple scoring model, we were able to quantify the agency rating grades, and find a satisfactory coherence between these ratings and the observed bank default rates. The mapping show a tendency of the agency ratings to aggregate default information into intermediate low category ratings, with an insufficient discrimination of the bank's default risk in these emerging market economies. Thus, the use of these agency ratings to map an bank's internal rating system for interbank risk management would give unsatisfactory results, with insufficient discrimination and precision of the bank's default risk.

By including regulatory and institutional factors into the scoring model, we enhance its statistical quality, but the aggregation of the default information into intermediate low quality grade remains. Notice that an alternative division of the estimated default probability distribution could alter these results. As we have seen for the rating model, other factors may need to be included into the scoring model, particularly macroeconomic and market structure.

[18]Testing several ratings models (including different new additional variables) and their intercepts significancy, as well as comparing the resulting reclassification tables is a work in progress.

APPENDIX

Appendix 1 Rated banks by country

Table 15: Frequencies of Moody's BFSR rated banks by country

Country	Code	N. banks	Frequency
Argentina	AR	40	8.28
Brazil	BR	52	10.77
Colombia	CO	23	4.76
Czech Republic	CZ	12	2.48
Ecuador	EC	8	1.66
Hong Kong	HK	6	1.24
Croatia	HR	4	0.83
Indonesia	ID	7	1.45
South Korea	KR	60	12.42
Latvia	LV	10	2.07
Mexico	MX	33	6.83
Malaysia	MY	20	4.14
Peru	PE	23	4.76
Poland	PL	46	9.52
Romania	RO	12	2.48
Singapore	SG	22	4.55
Slovenia	SI	2	0.41
Slovakia	SK	14	2.90
Thailand	TH	47	9.73
Taiwan	TW	6	1.24
Venezuela	VE	36	7.45
		483	100

Table 16: Frequencies of Fitch IR rated banks by country

Country	Code	N. banks	Frequency
Argentina	AR	16	6.23
Brazil	BR	26	10.12
Czech Republic	CZ	7	2.72
Hong Kong	HK	4	1.56
Croatia	HR	4	1.56
Indonesia	ID	4	1.56
South Korea	KR	42	16.34
Latvia	LV	4	1.56
Mexico	MX	24	9.34
Malaysia	MY	12	4.67
Peru	PE	1	0.39
Poland	PL	25	9.73
Singapore	SG	15	5.84
Slovenia	SI	1	0.39
Slovakia	SK	2	0.78
Thailand	TH	39	15.18
Taiwan	TW	6	2.33
Venezuela	VE	25	9.73
		257	100

References

Beaver, W., 1966, Financial ratios as predictors of failure, *Journal of Accounting Research* 4, 71–111.

Brister, B.M., R.E. Kennedy, and P. Liu, 1994, The regulation effect of credit ratings on bond interest yield : The case of junk bonds, *Journal of Business, Finance Accounting* 21, 511–531.

Cantor, R., and F. Packer, 1995, The credit rating industry, *Journal of Fixed Income* 5, 10–34.

——— , 1996, Multiple ratings and credit standards : Differences of opinion in the credit rating industry, Staff Report 12 Federal Reserve Bank of New York.

Carey, M., and M. Hrycay, 2001, Parametrizing credit risk models with rating data, *Journal of Banking and Finance* 25, 197–270.

Demirgüç-Kunt, A., 1989, Deposit-institution failures : A review of empirical literature, Economic Review 25 Federal Reserve Bank of Cleveland.

Ederington, L.H., J.B. Yawitz, and B.E. Roberts, 1987, The informational content of bond ratings, *Journal of Financial Research* 10, 211–226.

Ferri, G., L.G. Liu, and J.E. Stiglitz, 1999, The procyclical role of rating agencies: Evidence from the east asian crisis, *Economic Notes* 28, 335–355.

Fons, J.S., and A.E. Kimball, 1991, Corporate bond defaults and default rates 1970-1990, *Journal of Fixed Income* 1, 36–47.

Güttler, A., 2004, Using a bootstrap approach to rate the raters, Working paper University of Frankfurt.

Hamilton, D.T., P. Varma, S. Ou, and R. Cantor, 2004, Default and recovery rates of corporate bond issuers : A statistical review of moody's

ratings performance, 1920-2003, Special comment Moody's Investors Service, Global Credit Research.

Hand, J.R., R.W. Holthausen, and R.W. Leftwich, 1992, The effects of bond rating agency announcements on bond and stock prices, *Journal of Finance* 47, 733–752.

Honohan, P., 1997, Banking system failures in developing and transition countries : Diagnosis and predictions, Working Paper 39 Bank for International Settlements.

Jewell, J., and M. Livingston, 1999, A comparison of bond ratings from moody's, s&p and fitch ibca, *Financial Markets, Institutions and Instruments* 8, 1–45.

Kaplan, R.S., and G. Urwitz, 1979, Statistical models of bond ratings : A methodological inquiry, *Journal of Business* 52, 231–261.

Krämer, W., and A. Güttler, 2003, Comparing the accuracy of default predictions in the rating industry : The case of moody's vs s&p, Working paper University of Dortmund.

M., M. Crouhy, D. Galai, and R. Mark, 2001, Prototype risk rating system, *Journal of Banking and Finance* 25, 47–95.

Maddala, G.S., 1983, *Limited Dependent and Qualitative Variables in Econometrics* (Cambridge University Press).

Pinches, G.E., and K.A. Mingo, 1975, The role of subordination and industrial bond ratings, *Journal of Finance* 30, 201–206.

Poon, W.P.H., M. Firth, and H.-G. Fung, 1999, A multivariate analysis of the determinants of moody's bank financial strength ratings, *Journal of International Financial Markets, Institutions and Money* 9, 267–283.

Reiter, S.A., and D.A. Zeibert, 1991, Bond yields, ratings, and financial information : Evidence from public utility issues, *Financial Review* 26, 45–73.

Rojas-Suarez, L., 2000, Can international standards strenghten banks in emerging markets ?, Working paper Institute for International Economics.

——— , 2001, Rating banks in emerging markets : What credit rating agencies should learn from financial indicators, Working paper Institute for International Economics.

Shin, Y.S., and W.T. Moore, 2003, Explaining credit ratings differences between japanese and us agencies, *Review of Financial Economics* 12, 327–344.