Brunel University London
Department of Economics and Finance

Working Paper No. 13-02

Economics and Finance Working Paper Series

Omaima A. G. Hassan and Ray Barrell

Accounting for the determinants of banks' credit ratings

February 2013

http://www.brunel.ac.uk/economics

Accounting for the determinants of banks' credit ratings

Omaima A. G. Hassan and Ray Barrell

Brunel University

January 2013

Address for correspondence:

Professor Ray Barrell
Department of Economics and Finance,
School of Social Sciences,
Brunel University
Uxbridge, London
UB8 3PH
Ray.Barrell@Brunel.ac.uk

Dr Omaima Hassan
Department of Economics and Finance,
School of Social Sciences
Brunel University
Uxbridge, London
UB8 3PH
Omaima.Hassan@brunel.ac.uk

Acknowledgment

This paper has benefitted from comments from our colleagues in a seminar at the Brunel Business School and from Professor Frank Skinner and Dr Dilruba Karim. All error remain ours. We thank the Institute of Chartered Accountants of Scotland (ICAS) for a research grant provided to the principal author to conduct this research. We also thank Standard & Poor's for providing the credit ratings data at a marginal price to conduct this research.

Accounting for the determinants of banks' credit ratings

Abstract

The contribution of the banking industry to the recent financial crisis 2007/8 has raised public concerns about the excessive involvement of banks in risky activities. In addition there have been public concerns about the ability of credit rating agencies to evaluate these risks in advance. In this context, this study uses an ordered logit analysis to examine the determinants of banks' credit ratings using a sample of US and UK banks' accounting data from 1994 to 2009. Our intention is to examine to what extent banks' ratings reflect banks' risks. Our analysis shows that a small number of accounting variables, namely: bank size, liquidity, efficiency and profitability are able to correctly assign credit rating for approximately 74% to 78% the sample banks. Surprisingly, the association between banks' credit ratings and each of leverage asset quality and capital is not robust, suggesting that the rating agency's models did not pick them up despite their importance in the crisis. In addition, the relationship between banks' credit ratings and liquidity is the reverse of that which an adequate early warning system would require. As banks benefit from higher credit ratings they will have addressed their determinants rather than taking care of systemic factors that affect underlying risk. Policy makers therefore need to intervene to address this market failure.

Key words: banks credit rating; ordered probit model; accounting information.

1. Introduction

Credit rating agencies (CRAs) formulate and issue credit ratings for both companies (debt issuers) and individual debt instruments. Issuer' rating represents a forward-looking assessment of the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time. Therefore, credit ratings are considered to be important drivers of a firm's cost of finance, its capital structure and ability to continue trading (Gray et al., 2006). CRAs draw on publicly available information, private information and their own judgement to create issuers' ratings.

Issuer's credit ratings are therefore interesting since they represent the judgement of informed and sophisticated financial analysts about a firm's credit worthiness. However, the main drivers and assumptions underlying these ratings are not publicly disclosed (Frost, 2007). In addition, there is a dearth of prior studies that examines issuers' credit ratings in general and in the financial service sector in particular. Most of studies of ratings focus on determinants of bond ratings, default probablities or the reliability of credit ratings. Furthermore, very recent prior studies that focused on banks (e.g., Bissoondoyal-Bheenick and Treepongkaruna, 2011; Bellotti et al., 2011a; 2011b; Shen et al., 2012; Öğüt et al., 2012) vary in terms of the purpose of the study, the type of credit rating used, the explanatory variables included in the model, the statistical analysis used. To date, no generally accepted model exists as to what determine CRAs perceptions of banks' credit worthiness. The current study tries to fill this gap in the literature by examining the accounting determinants of credit ratings of banks in two major markets where the recent financial crisis of 2007/08 is believed to have started: i.e. the US and the UK.

During the 2007/8 banking crisis, credit ratings are believed to have played a key role in this crisis (House of Commons' report, May 2009). On one hand, it is argued that CRAs misled market participants by failing to reflect the difficulties faced by the banks in their ratings. On the other hand, market participants seemed to over-rely on these ratings for investment decision making (Bissoondoyal-Bheenick and Treepongkaruna, 2011) as it was assumed they were efficient processors of available information. This study tries to explore whether banks' credit worthiness reflect banks' basic risk characteristics. Our results indicate that banks' credit ratings rely heavily on bank size, profitability and efficiency as indicators of banks' credit worthiness. However, Barrell et al. (2010) and Haldane and Madouros (2012) find that these variables are not associated with either systemic risks or individual bank risks and hence the ratings agencies did not in general provide an adequate early warning system. In addition, less liquid banks are found to have higher ratings and the results show no robust relationship between banks' credit ratings and each of asset quality, capital adequacy ratios and leverage. These results are surprising since inadequate capital, lack of liquidity and poor quality loans led many banks to collapse recently from 2007 – 2011. These results indicate that the ratings seem to reflect a perception of potential profit rather than potential risk and that the ratings agency models did not pick up much of the cause of the crisis

If banks' credit ratings do not in fact reflect risk, a change in regulation might be necessary, with reduced reliance on ratings agencies and even on risk weighting, in the policy framework. This may mean it would be wise to move away from the arrangements under the Basel II agreement, whereby banks can use credit ratings on their assets from approved CRAs when calculating their net regulatory capital reserve requirements. The more risky a bank's portfolio is judged to be, the more reserve assets it must hold, and if it is heavily invested in highly liquid and low risk securities, the less it needs to hold as capital in reserves. If the ratings were wrong then capital levels may well have been inadequate as a result.

The remainder of this paper is organised as follows. In section 2, we discuss related literature. Section 3 develops the ordered logit model that we use to map accounting variables to credit ratings data and the construction of our explanatory variables. Section 3 describes the research sample, the results are then discussed in section 5 and section 6 provides concluding remarks.

2. Literature review

Credit ratings are claimed to be forward-looking opinions about the ability and willingness of an issuer to meet its financial obligations in full and on time. CRAs rely on public information such as financial statements and non-public information derived from discussions about the management, planning and strategy of the company as well as subjective judgements by analysts to assign quality ratings either to bonds or issuers. Therefore, CRAs are generally dubious about the ability of economic models to capture the details of their credit rating and corporate bankruptcies (Kaplan and Urwitz 1979). However a number of prior studies have done a good job in explaining and predicting bond ratings and corporate bankruptcies as a function of a relatively small number of historically and publically available information (e.g., Altman, 1968; Kaplan and Urwitz, 1979; Holthausen and Leftwich, 1986; Hand et al., 1992; Altman and Rijken, 2004).

Prior studies on credit ratings as such can be classified into two main streams. The first stream of research (e.g., Altman and Saunders, 2001; Amato and Furfine, 2004; Iannotta, 2006; Shen et al., 2012) tries to examine the reliability of ratings. For example, Shen et al. (2012) investigates why rating agencies issue different ratings for banks with similar financial performance but from different countries. The second stream of research tries to explore determinants of different types of ratings: sovereign ratings (e.g., Cantor and Packer, 1996; Afonso, 2003; Bissoondoyal-Bheenick, 2005; Bennell et al., 2006), bond ratings (e.g., Kaplan and Urwitz, 1979; Blume et al., 1998; Iskandar-Datta and Emery, 1994; Molinero et al., 1996), issuer ratings (Poon et al., 1999; Gray et al., 2006; Bissoondoyal-Bheenick and Treepongkaruna, 2011; Bellotti et al. , 2011a , 2011b; Öğüt et al., 2012) and default probabilities (e.g., Altman, 1968; Altman et al., 1977; Shin and Lee, 2002; Ahn and Kim, 2009; Chaudhuri and De, 2011, Bonfim, 2009; Liao et al., 2009). Our study is related to the second stream of research that examines determinants of issuer (bank) ratings and we discuss it in greater depth in the rest of this section.

Bellotti et al. (2011a; 2011b) examine the impact of financial variables, the year in which the rating was made and country specific dummy variables (89 country dummies), on individual bank ratings produced by Fitch using two techniques: a data mining technique (support vector machines (SVM) and multivariate techniques (ordered probit and ordered logit models). The main purpose of Bellotti et al. (2011a; 2011b) is to compare the ability of ordered choice models and support vector machines in modelling and predicting international bank ratings. The financial ratios used include the ratio of equity to total assets, the ratio of liquid assets to total assets, the natural logarithm of total assets, the net interest margin, the difference between the ratio of operating income to total assets and the ratio of operating expenses to assets, the ratio of operating expenses to total operating income and the return on equity. Using data on 681 international banks' ratings between 2000 and 2007, Bellotti et al. (2011a; 2011b) find that ratings reflect a bank's financial position, the timing of rating assignment and a bank's country of origin. Bellotti et al. (2011b) also find that the ordered choice models unambiguously identify the equity to total assets, the natural logarithm of total assets and the return on assets to be the most significant determinants of ratings. In addition, there is strong evidence that a bank's country of origin has a significant influence on bank ratings. Although SVM are found to produce considerably better predictions of international bank ratings than ordered choice models due to its ability to estimate a large number of country dummies unrestrictedly, Bellotti et al. (2011b) argue that the ordered choice models are more reliable for this, since they yield more consistent results when modelling determinants of individual bank ratings.

Poon et al. (1999) develop a model to explain bank financial strengths ratings issued by Moody's using accounting variables and financial ratios of the banks. A total of 100 variables and ratios are collected for each bank to cover the major measures of profitability, efficiency, asset composition, interest composition, interest coverage, leverage and risk. Poon et al. (1999) use factor analysis to identify the important underlying constructs that explain bank financial strengths ratings. Three factors are found to account for over 50% of the variability in the data set and they are used in the ordered logit model (cross-section analysis). Using a sample of 130 banks from 30 countries Poon et al. (1999) find that the loan provisions is the most important factor to explain bank financial strengths ratings, followed by risk, and then profitability. These three factors are able to correctly predict 63.1% bank financial strengths ratings. Country risk ratings do not appear to be significant determinant of bank financial strengths ratings. While the models achieved good predictive power, the best model includes traditional short-term and long-term debt ratings. This suggests that banks' financial strengths ratings may not be adding very much information over and above that contained in traditional debt ratings.

The current study is also related to the investigation of Shen et al. (2012). Although, Shen et al. (2012) investigate why rating agencies issue different ratings for banks with similar financial performance but from different countries (the reliability of ratings), they employ an ordered logit model of long-term bank ratings issued by S&P for a sample of 3347 bank-year observations from 86 countries during 2002–2008 using financial ratios, sovereign credit ratings and different measures of information asymmetry. Their model includes financial ratios[1] about bank's profitability, liquidity, capital, efficiency and asset quality. It also includes bank size and sovereign credit ratings as control variables. Countries are divided to those with low and high information asymmetry. The results demonstrate that without considering the effect of the asymmetric information; the five financial ratios show the expected influences on ratings. But when employing different measures of information asymmetry, the results show that in countries with low information asymmetry, the influences of financial ratios are strengthened, whereas they are weakened in countries with serious asymmetry. This result applies to all financial ratios except for the capital ratio. Shen et al. (2012) explain this result by the heavy weight that credit rating agencies assign to the Capital ratio even in a country with severe information asymmetry.

Öğüt et al. (2012) try to forecast bank financial strength ratings for a sample of 18 Turkish banks from 2003 to 2009 issued by Moody's using 26 financial and operational ratios. Öğüt et al. (2012) use different techniques: data mining techniques (SVM and Artificial Neural Network) and multivariate techniques (multiple discriminant analysis and logit model) to estimate a suitable model and to compare the performances of these different techniques in estimating bank financial strength ratings. The purpose was to determine the variables that play an important role in assigning the ratings. Öğüt et al. (2012) find that the ordered logistic classifier performed better as compared to other classifiers when factor scores are used as input variables while multiple discriminant analysis and SVM achieved the highest accuracy rates when raw variables are used as input variables. The accuracy rates of all classifiers are higher when variables rather than factor scores are used as input. Öğüt et al. (2012) find that the most important financial factors are efficiency, profitability and the proportion of loans in the assets.

One closely related prior studies to ours is Bissoondoyal-Bheenick and Treepongkaruna (2011) who analyse the quantitative determinants of banks' ratings, provided by Standard & Poor's, Moody's, and Fitch for a sample of 49 commercial UK banks and 20 commercial Australian banks for the period 2006 to 2008. Using an ordered probit model, Bissoondoyal-Bheenick and Treepongkaruna (2011) find that

[1] Profitability: the average ratio of net income to total assets over the past three years; Liquidity: the average ratio of liquid assets to deposits and short-term funding; Capital: the capital adequacy ratio as defined by the Bank of International Settlement; Efficiency : the average ratio of cost to income; Asset Quality: the average ratio of loan loss provisions to net interest revenues.

asset quality, liquidity risk, capital adequacy and operating performance are the key determinants of banks' ratings across the rating agencies. In addition, market risk and macroeconomic variables such as gross domestic product and inflation are found to be insignificant factors in explaining banks' ratings. However the authors use annual financial data to explain both short-term and long-term rating, but these data might be less effective in explaining long-term issuer ratings. This is because long-term ratings should reflect long-term perspective rather than most recent observations about the bank. In addition, these ratings are from different credit rating agencies with different ratings' methodologies which might be captured by different financial variables. This might explain the very low percentage of correct ratings calls obtained in Bissoondoyal-Bheenick and Treepongkaruna (2011), when forecasting long-term ratings for a sample of banks in 2009. In addition, using a scale for rating from 1 to 21 and from 1 to 9 might have affected the results since banks' ratings tend to be clustered around specific rating region such as A+/AA- for S&P.

In sum, very recent prior studies that focused on banks vary in terms of the purpose of the study, the type of credit rating used (the dependent variable), the explanatory variables included in the model and the statistical analysis used. To date, no generally accepted model exists as to what determine CRAs perceptions of banks' credit worthiness. The current study tries to fill this gap in the current literature by examining the accounting determinants of credit ratings of banks in two in the UK and the US where CRAs are believed to have played a key role in this crisis.

Prior studies suggest a number of company characteristics to influence credit ratings such as: firm size, leverage, profitability, liquidity, growth, interest coverage, systematic risk, unsystematic risk. However, Philips (1975) and Ross (1976) suggest that credit analysts rely heavily on numbers produced by the firm's accounting system rather than from the stock market. In addition, studies such as Bissoondoyal-Bheenick and Treepongkaruna (2011) find an insignificant effect of market risk and macroeconomic factors on banks' ratings. We emphasise that macroeconomic variables such as market risk are also important factors in determining banks' ratings but banks cannot control these factors. The current study, however, is interested in exploring banks' specific characteristics that banks can control in order to improve their ratings relative to the other banks operating in the same environment. Therefore, the current study relies mainly on accounting information to explain credit ratings of banks in the US and the UK markets, namely: bank size, leverage, profitability, efficiency, liquidity, asset quality (risk) and capital adequacy. In the following section we explain the nature of a banking business and how banks' characteristics can drive banks' credit ratings.

3. The research model

It is useful to look at factors[2] that might affect the riskiness of a bank in order to assess whether CRAs are taking these factors into account in setting their ratings. Banks take in deposits (D) in some form, on which they pay interest at a rate r_d, and make loans (L) or enter into other credit provision arrangements on which they charge interest r_l. Depositors may randomly demand cash and hence some low-risk liquid assets (LA with a rate of return r_{ra},) have to be held, with $r_d - r_{ra}$ the cost of liquidity. The appropriate (on-book) liquid asset ratios will depend on the variance of deposits (var(D)), their maturity composition and on the availability of off-book, or wholesale market, liquidity. We may write the asset side of the bank's balance sheet (AS) as

$$AS = L + LA \text{ where } LA/D = f(var(D), wholesale) \qquad (1)$$

When banks make loans they take risks, and the loan book will face a default rate that will vary over time with economic conditions. The expected default rate (b) is included in the spread between borrowing and lending rates, which will also include administrative costs (ad) and payment for risk taking (rp):

$$r_l = r_d + b + ad + rp \qquad (2)$$

We may re-write this as an expression for the Net Interest Margin (NIM) which is the lending rate r_l less the deposit rate r_d

$$NIM = b + ad + rp \qquad (3)$$

[2] See Table 2 for a summary of the factors included in the research model and their definitions.

Given that banks may make larger-than-anticipated losses on their loan portfolio in some periods, they have to carry both contingency reserves (provisions) and finance some of their loan book with capital (K). In the absence of regulation, the amount of capital held by a bank will depend on the variance of loan losses (var(BL)) and on the cost of generating capital. The larger the quantity of capital relative to loans (K/L), the lower the probability of bankruptcy for a given var(BL) and hence the higher should be the CRAs rating. A bank may be concerned with the probability of default, and for a given var(BL) it may choose its level of capital to ensure that there is a reasonable distance to default in terms of the number of standard deviations the equity base will cover. The classic form of capital is equity. Additional loss-absorbing capacity can be provided by subordinated debt, (SD with cost r_{sd}) although since it is an obligation it does not protect against bankruptcy in the way that equity does. Chami and Cosimano, (2003) assert that Tier 2 capital in the form of subordinated debt may have positive benefits in terms of market discipline. It is argued that unlike equity, there may be alignment of the interests of subordinated debt holders with deposit insurers, creating incentives for bankers to disclose information to the market and hence the visibility of financial distress signals provided by subordinated debt spreads over the risk free rate. However, Levonian (2001) suggests that increasing subordinated debt raises risk in banks, and hence the CRAs evaluation should change with the mix of equity and subordinated debt[3]. The liabilities of the bank may be written as

$$LS = EQ + SD + D \qquad (4)$$

The gross profits (Π_g) of the bank after allowing for current charge-offs (BL) may be written as

$$\Pi_g = r_l L + r_{ra} LA - r_{sd} SD - r_d D - BL - ad L \qquad (5)$$

If bad loan provisions (bL) exceed charge offs (BL) then the bank can build its provisions P with (bL – BL) or pay out some proportion (β) of the gain (or claw back a loss) in current profit. Profits (Π) may then be written as

$$\Pi = \Pi_g + \beta (bL - BL) - (bL - BL) \qquad (6)$$

[3] See also Evanoff and Wall (2000)

Hence the higher the gross profit of the bank, the easier it should be to absorb losses and hence the higher its credit rating by the CRA should be. The pure capital of the bank (K), all else equal, is its capital base plus its provisions, and abstracting from new issues of equity or of subordinated debt, capital evolves in relation to profit retentions ($\gamma\Pi$) and excess provisioning (1- β) (bL – BL), with (-1) indicating previous period values.

$$K = EQ + SD + P \quad = EQ(-1) + \gamma\Pi + SD(-1) + P(-1) + (1-\beta)(bL - BL) \qquad (7)$$

In this context, a failure might emerge either because a bank does not have enough on-book liquidity to meet the needs of depositors, and cannot access the wholesale market, or because loan losses have built up to the point where capital is expected to be exhausted. The higher is LA/D for a given var(D) the less likely is a liquidity crisis, and the higher K/L or (EQ+SD)/L for a given var(BL) the less likely a solvency crisis will emerge. Hence their impact on the CRAs rating should be clear.

The size of a bank may also be taken in to account when setting ratings. If there is an extreme cost involved in bankruptcy then the bank will plan to keep expected losses below a floor. Risk may be taken on until the distance to default, measured by K/sd(BL) = z_f reaches a ceiling, where sd(BL) is the standard deviation of loan losses. This is the acceptable risk of catastrophic failure. Let us assume that risks are normal and that the acceptable probability is 0.001, much as is discussed in Zhu (2008). Then the bank may take on additional more risky loans and assets until its (maximum) expected loss is no higher than $X_m = z_f^* * SD$ where the target for z_f^* is approximately 3.3 for a 0.001 probability. We may describe expected losses bL as

$$bL = h(X_m, \text{size}, J) \qquad (8)$$

where the derivative with respect to X_m is negative, that with respect to size is negative because of the covariance of risks in the portfolio and positive in J which is the set of other factors affecting expected losses that will depend on decision making by the bank. This will include both its level of capital and the structure of that capital in terms of Tier 1 and Tier 2. In a world of exogenous risk we would expect that sd(BL) would decline with size, and hence larger banks could have a lower level of capital for a given distance to default (dtd or z_f^*), or for a given level of the capital ratio they should have a higher rating from the CRAs.

There is an extensive literature based on Merton (1977) on moral hazard for large banks, where size might generate an implicit 'too big to fail' guarantee. The implicit insurance from 'too big to fail' means that large banks have an incentive to lower capital adequacy. Demsetz and Strahan (1997) in a study of US banks found that, though larger bank holding companies are better diversified than smaller ones, they do not translate this advantage into less total risk. Rather, larger banks use their diversification advantage to operate with lower capital ratios and pursue riskier strategies, with greater concentrations of consumer and industry loans and exposure to systematic risk. Indeed, as Haldane and Madouros (2012) suggest there is no strong evidence to indicate that larger banks are less risky investments, except for the fact that they may be too large to be allowed to fail. Size and losses in the recent financial crisis (2007-2008) do appear to be positively related though.

Consistent with prior studies and S&P's methodology we model credit ratings as a function of a number of accounting variables capturing the core features of the analysis above. Therefore we model banks' rating as a function of bank size, leverage, profitability, efficiency, liquidity, asset quality (risk) and capital adequacy ratios. So the research model we are trying to examine in this paper is as follows:

Long-term bank's credit rating = *f* (bank size, leverage, profitability, efficiency, liquidity, risk, capital adequacy). (9)

A bank's long-term credit rating in our model is a discrete variable that takes a finite number of values ranges from AAA to D. These finite values have a natural ordering. Thus it possesses the characteristics of an ordinal scale. For example, AAA rating is higher than AA rating which is higher than A rating and so forth. Furthermore, these values are not necessarily evenly spaced. For example, the difference between A and BBB ratings does not necessarily equal the difference between BBB and BB ratings. These characteristics of the credit rating variable affect the statistical technique that can be used to explain and predict it. For example, ordinary least-squares regression estimation (OLS) would be inappropriate because the use of an ordinal dependent variable in a regression analysis violates the statistical assumptions of OLS. Therefore a form of an ordered discrete dependent variable technique is preferred[4] to tackle these problems. This is why we employ the ordered logit model to explain banks' rating in the current study following Kaplan and Urwitz (1979), Blume et al. (1998), Gray et al. (2006), Poon et al. (1999) and Shen et al. (2012).

4. The Research sample

Long-term domestic issuer credit ratings for all UK and US banks rated by Standard & Poor's over the period from 1994 to 2010 (206 banks) constitute the initial sample for this research. Concurrent annual financial information for the period 1994 to 2009 was collected from the BankScope database. The BankScope database has a standardised format for financial statements which makes data comparable over time and between banks that adopt different accounting standards. We use two information concepts with regard to credit rating, with the first being forward looking and the second being backward looking, using published information. We define an annual financial report to be contemporaneous with the rating if it relates to the financial year-end that occurs within six months after the rating and hence our analysis of the ratings reflects forward-looking information. Alternatively if the annual financial report was published in the twelve months prior to the rating then our analysis of ratings reflects historical information. This is to ensure that any changes based on information released in the annual report are captured in the corresponding rating and also to examine the ability of credit ratings to capture financial information that are about to be released in the near future.

We, therefore, create two different variables for banks' credit worthiness: (i) CR6FOR: credit ratings takes place six months before the financial year-end assuming that credit ratings reflect forward-looking information, and (ii) CR12BK: credit ratings obtained within 12 months after the financial year end. Both measures of credit ratings are ordered as follows: banks rated [AAA; AA] takes the value of 3. Banks rated [AA-; A+; A] takes the value of 2 and banks rated [A-; BBB+; BBB; BBB-] takes the value of 1. Banks that are rated less than BBB [from BB+ to D] were few and were dropped from the final

---

[4] See Kaplan and Urwitz (1979, p.236).

sample, which restricts our sample to banks with ratings that are considered to be investment grade only. In addition, credit ratings for which financial information was unavailable were excluded from the final sample. This leaves us with a final sample of 85 banks [27 UK banks and 58 US banks]. The number of observations per bank ranged from three to nine observations over the period 1994 to 2009 due to missing data.

We created a number of measures for each accounting variable using BankScope database. This process ended up with a total number of 36 measures of the different bank characteristics: five for size, five for profitability, five for leverage, four for efficiency, six for liquidity, five for asset quality (risk) and six for capital adequacy ratios. In assigning credit ratings, CRAs such as S&P adopt a methodology known as 'rating through the cycle' that takes a long-term perspective about the firm. In particular, when assigning long-term credit rating, S&P considers three-year averages of relevant financial ratios rather than just the most recent observations. Therefore, all accounting variables in the current study are computed using a three-year arithmetic average of the annual data (Blume et al., 1998; Gray et al., 2006). Given the time frame and the number of banks in our sample, a further reduction in the number of variables was desirable. This is particularly necessary as the variables within each set are summarising essentially the same underlying information and hence are generally strongly collinear. In order to extract the underlying structure we applied principal components analysis[5] to each set of measures in order to be able to summarise their characteristics.

We can express the concept mathematically as follows. If we take a set of n related variables X available over the time period t we can calculate the n*n correlation matrix XX' which will have n eigenvetors in a matrix V associated with n eigenvalues (or weighting factors) λ_i. Each principal component (or eigenvector) summarise an orthogonal component of the correlation matrix, and represent a weighted

---

[5] Principal component analysis is a variable reduction procedure. It is useful when you have data on a number of variables which are measuring the same construct, which means that these variables are correlated with one another. We may wish to reduce the observed variables into a smaller number of principal components (artificial variables) that will account for most of the variance in the observed variables, or we may wish to find which of the set of raw variables can be seen as summarising the others. The principal components or the dominant variables may then be used as predictor or criterion variables in the subsequent analysis.

combination of each of the elements. We may judge the importance of the component (ranked form 'most to least) by proportion of the covariance matrix it summarises, and we can judge the importance of each variable in the set of data to the vector by its weighting. Table 1 gives the first two principal components for each of our seven data sets and excludes the others, and it also reports on the cumulative proportion of XX' that the component explains. In all cases the first component summarises over a third of the variance in the observed variables, whilst the first two summarise over 60 percent. Therefore, we decided to investigate two sets of models based on the outcomes of the principal component analysis: a parsimonious one based on the highest weighted element of the first principal component only, and a more general model that is based on the highest weighted elements in the first two principal components as shown below.

CR= *f* (*Assets1, Assets5, Leverage3, Leverage5, Profit2, Profit3, Efficient4, Efficient1, Liquid1, Liquid3, Risk3, Risk5, Capital3, Capital5*) (10)

Table 2 describes these variables in detail and the expected direction of a relationship between each explanatory variable and the dependent variable.

5. Research results and discussion

The purpose of the current study is to examine to what extent banks' ratings reflect banks' basic characteristics revealed in its publically available accounting information, and to determine to what extent banks' ratings reflect banks' risk. We examine our research models using a multivariate ordered logit analysis and then look at the predictive capacity of these models. We have two dependent variables, a backward and a forward looking rating and two potential time periods (because it is claimed that CRAs raised their standards in assigning ratings in mid- 2001), as well as a parsimonious and a general model, giving us 8 possible models to choose between. There are several criteria we could use for doing this, but we emphasise the efficiency in allocating the sample banks correctly into the relevant ratings' categories, with a strong emphasis on the need to be able to correctly classify banks with low ratings. In addition, we look to see which variables are significant in our analysis, testing for the deletion of insignificant ones. This allows us to evaluate the models in terms of their inclusion of significant crisis driven variables. We first describe the data set and the correlations between variables. Then we discuss the results of the multivariate analysis.

5.1 Descriptive analysis

Table 3 shows both the descriptive analysis of each explanatory variable under the two dependent variables and for each rating category. It also shows the descriptive statistics by rating category for a number of accounting variables that are found to be relevant to the credit rating process from the principal component analysis. Table 3 shows that banks in the sample vary on average from small (average total assets of 15,617 to 447,834 mil USD) to very big banks. Banks in our sample have average interest-bearing liabilities divided to average earning assets ratio (*Lev5*) of 71% but very low leverage ratio represented by Lev3. On average, the sample banks have a cost to income ratio of 57% (*EFF1*) and an average ratio of 4.2 % of non-interest expenses to average assets. The sample banks have on average a ratio of net loans to total of 61% (*LIQ1*) but a ratio of loans to customer deposits of 117% (*LIQ2*). The net charge off or the amount written-off from loan loss reserves less recoveries to gross loans is on average 99% (*Risk3*) but the average growth of gross loans of a bank to the total growth of gross loans of the sample banks is 0.01%. Banks in our sample have an average ratio of equity to total assets of 12% (*CAP3*) with a very low subordinated debt to total assets ratio (*CAP5*) of 2 %.

5.2 Correlation matrix

Table 4 shows Pearson Correlations results between measures of credit ratings and a number of accounting variables which proxy for firm size, liquidity, efficiency, profitability, leverage, risk and capital for a sample of US and UK banks. The results show that credit ratings have a significant positive association with both measures of bank size (*Assets1 and Assets5*) as expected, which indicates that larger banks have higher credit ratings. No relationship with *leverage3* is found but a negative and significant association with *leverage5* is documented, which indicates that highly levered banks have lower credit ratings. Contrary to our expectations, profitability measures have in general a negative and significant relationship with banks' credit ratings. However this is a univariate analysis, which suffers from potential omitted variables. The association with both measures of efficiency is negative and significant, which indicates that banks that are able to drive their costs down relative to other banks may be perceived to be more efficient and are awarded higher ratings.

The results also show a negative and significant correlation between bank's rating and *liquid1* which indicates that higher rated banks have lower net loans to total assets ratio. Contrary to our expectations, the correlation between banks' ratings and liquidity is positive when we consider the ratio of net loans to customers' deposits (*liquid3*) but less robust since it is not significant with our measure of forward-looking ratings. In general, no association is found between the two measures of banks' risk and credit rating except that *Risk3* shows a negative and significant association with backward-looking banks' ratings, which means that lower charge off indicate lower risk for banks and higher ratings. The correlations suggest that the higher the equity to total assets ratio (*capital3*) of a bank the lower the credit rating but the higher the subordinated debts to total assets the higher the banks' rating. In addition, the correlations between the explanatory variables do not indicate that multicollinearity problem forms a significant problem for our models. This in part reflects our pre-selection using principal components so that variables within a subset should be largely independent of each other.

5.3 Regression results

We employ the logit regression technique to regress measures of bank size, leverage, profitability, efficiency, liquidity, risk and capital on each measure of the dependent variable. In each case we estimate a minimal model which includes the highest weighted measure in the first principal component for each variable. In addition, we estimate a maximal model that includes the highest weighted measures in the first two principal components for each variable. For forward-looking rating the minimal model is:

$$\beta X_{it} = a + b1\ Assets1_{it} + b2\ Leverage3_{it} + b3\ Profit2_{it} + b4\ Efficient4_{it} + b5\ Liquid1_{it} + b6\ Risk3_{it} + b7 Capital3$$

Whilst the maximal model (denoted with a *) is

$$\beta^* X^*_{it} = a + b1\ Assets1_{it} + b11\ Assets5_{it} + b2\ Leverage3_{it} + b21\ Leverage5_{it} + b3\ Profit2_{it} + b31\ Profit3_{it} + b4\ Efficient4_{it} + b41\ Efficient1_{it} + b5\ Liquid1_{it} + b51\ Liquid3_{it} + b6\ Risk3_{it} + b61\ Risk5_{it} + b7 Capital3_{it} + b71 Capital5_{it}$$

See Table 2 for a summary definition for all the variables. For the backward-looking rating model we change the dependent variable to $RT12BK_{it}$. We run these two regressions for the full sample period [1994 to 2009] and for a shorter period [from 2002 to 2009] because it is claimed that CRAs raised their standards in assigning ratings in mid- 2001 (Gray et al., 2006; Cheng and Neamtiu, 2009). Each set of results reports on the Akaike information criterion (AIC) as well as the pseudo R squared, and contains a table summarising the classification of the dependent variable into predicted asset clasess. Although we do not set out an explicit cost function for choosing between models, we are looking to maximise the quality of the fit, with the percent correct in category 1 (lowest rated banks) and 3 (highest rated banks) carrying more weight than category 2 which would anyway be the default in a no information analysis as most banks are in that category.

Table 5 shows the results of four regression models for the full sample period [1994-2009] with both the maximum and the minimal regression models for the two dependent variables [backward-looking rating and forward-looking rating]. The results suggest a positive and highly significant relationship between bank size (*Asset1 and Assets5*) and bank's rating as expected and consistent with results from prior studies (e.g., Bellotti et al., 2011a; 2011b; Shen et al., 2012). As discussed above, this may have been a misperception of the risks and the strategies undertaken by large banks, and can be considered a misclassification of risk by the CRAs. The results also show that leverage does not have a relationship with banks' credit ratings except for the maximum regression model with forward-looking ratings. Again the lack of attention to leverage can be seen as a misclassification of risk by the CRAs. Profitability in general shows positive and significant relationship with banks' credit ratings as expected, except that the net interest margin before provisions (Profit2) has a significant but negative relationship with banks' backward-looking rating which contradicts our former expectations. The results also show a negative and highly significant relationship between banks' credit rating and banks (lack of) efficiency measured by the ratio of cost to income (efficiency 1) as expected and consistent with results from Shen et al. (2012). The results for non-interest expenses relative to assets (efficiency4) are generally in line with our expectations with the exception that backward rating exhibits a positive and significant relationship. The results for bank efficiency indicate that more efficient banks which are able to drive their costs down relative to other banks are awarded higher ratings.

The results also show a negative relationship between banks' ratings and their liquidity in terms of the ratio of net loans to total assets (*Liquid1*) but this is only significant for the minimal models, consistent with results from Bissoondoyal-Bheenick and Treepongkaruna (2011) and Shen et al. (2012). However, contrary to our expectations and to results from prior studies, the results show a positive and highly significant relationship between the ratio of net loans to customer deposits (*liquid3*) and banks' ratings This result indicates that less liquid banks, which might be more profitable in the short run, were rated more highly which is surprising since banks' lack of liquidity is a major risk and it was an important reason for systemic problems which contributed to the recent financial crisis 2007/08 (Barrell et al., 2010). Finally, the results show no relationship between banks' credit rating and either bank's risk or capital adequacy ratios. This latter result is surprising as well since capital adequacy forms a buffer against loan losses, and it was inadequate capital that led many banks to collapse recently from 2007 – 2011. These results for liquidity and capital adequacy indicate that the ratings agency models did not pick up their importance and hence missed much of the cause of the crisis. In general the ratings seem to reflect a perception of potential profit rather than potential risk.

In addition the results also show that these four models are able to replicate 68 to 77 percent of the assigned ratings of our sample banks, but in general, the maximum models perform better than the minimum models in terms of the total hit ratio. The default choice category would be category 2, as this is where the majority of banks are located, and our maximal model can pick up 44 to 57 percent of the banks that are assigned to category one. This is particularly important for investors as lower graded banks require more coverage. The minimal model picks up only 11 to 14 percent of the banks that are allocated to the lowest category. If the model user is risk averse then they will have a strong reason to choose the maximal model as it picks up weaker banks (in terms of their credit ratings).

We re-run the analysis for a shorter period [from 2002 to 2009], because it is claimed that CRAs raised their standards in assigning ratings in mid- 2001 (Gray et al., 2006; Cheng and Neamtiu, 2009). Table 6 shows the results of four regression models for the shorter sample period. The results are generally similar to those obtained for the full sample period, but the Pseudo R squared is noticeably higher in each case, suggesting the model fit is significantly better over the shorter period. In the forward looking maximal model the two size related assets variables remain significant, whilst the net interest margin after allowances (*Profit2*) has a negative impact, suggesting the agencies considered high profitability was associated with more risk taking. The (lack of) efficiency indicator (costs to income) remains negative and significant, as we would expect. The ratings agencies rewarded banks who relied on the wholesale market for liquidity (one way of interpreting the *Liquidity 3* indicator) with a higher rating, which was perhaps unwise as some of the first banks to fail in the 2007-2011 crisis were those, such as Northern Rock, who depended heavily on that market. Over this shorter period it becomes clear that ratings agencies were taking account of equity in banks and that those with more equity (*capital3*) were rewarded with higher ratings.

The backward looking model is similar to the forward looking one, but there is no significant role for capital in the maximal backward model. The maximal models are noticeably better than the minimal models in terms of their hit ratio for the highest and lowest rated banks and this suggest that the ratings agencies were using a wider information set to grade these banks, and this is more easily picked up with our two principal components model. Between 70 and 80 per cent of the lowest rated banks are picked up by this accounting information based model, with 53 or 65 per cent of the highest rated banks being picked up. This would suggest that the agencies used non-accounting information in their ratings decisions more heavily in the case of good banks (as they perceived them) than bad banks.

As a robustness check, we test for the inclusion of variables that were consistently insignificant for the same model for the same sample period using Wald test as shown in Table 7. If the Wald test is significant (the p-value is below .05), then we would conclude that the parameters associated with these variables are jointly significantly different from zero, so that the variables should be included in the model. The results show that the variables we have tested for the different models are jointly not different from zero, therefore we should exclude them from the model. However, these variables are jointly different from zero in the Maximum model for the shorter sample period for the forward-looking rating.

Therefore, dropping these variables from the model would result in a loss of information and affects both Pseudo R-squared and the fit ratio of the model. Therefore, we keep them in the model.

To sum up, our results show a robust significant positive relationship between banks' credit ratings and bank size (*Assets1*) consistent with results from Bellottie et al. (2011a; 2011b), indicating that larger banks receive higher ratings. The results also show a robust significant negative relationship between banks' ratings and (in) efficiency (*Efficiency1*) consistent with results from Öğüt et al. (2012). Contrary to our expectations, a robust significant but positive relationship between banks' ratings and lower liquidity (*Liquid3*) is documented. In addition, the results show that banks' credit ratings do not seem to consistently pick up the effect of capital adequacy, leverage, profitability and bank risk. Further tests prove that these variables are jointly significant for the process of credit ratings, in particular the forward-looking ratings.

6. Concluding remarks

This study contributes to the current literature on credit risk and on financial institution by examining banks' characteristics that derive banks' credit ratings for a sample of US and UK banks. Our analysis shows that a small number of accounting variables, namely: bank size, liquidity, and efficiency have robust association with banks' credit ratings. The results also show that our model performs better for the sample period 2002 to 2009 and is able to correctly assign credit rating for approximately 74% to 78% the sample banks. Moreover, our analysis shows that these accounting variables are better able to explain the forward-looking ratings for the highest rated banks but the backward-looking ratings equations are best for replicating the lowest rated banks ratings. This might indicate that CRAs were more conservative when assigning ratings for the lowest rated banks and relied on historical accounting information. Our results also show that the maximum models worked better than the minimum models in terms of Pseudo R-squared and the hit ratios for the highest and lowest rated banks which suggest that CRAs rely on a wider set of information in assessing banks' creditworthiness. However, this study is limited to the publicly available accounting information only, though issuer credit ratings is claimed to capture both publicly available and private information both quantitative and qualitative.

Some interesting and perhaps surprising results are obtained from the current study. The main result is the lack of association between ratings and leverage and capital adequacy. In addition, the relationship between banks' credit rating and liquidity is the reverse of that expected, with less liquid banks in terms of the ratio of loans to customer deposits being associated with higher ratings, despite the problems of wholesale market dependence implied during the 2007-8 crises. We would posit that the CRAs were rewarding the efficient use of funds without looking fully at the risks involved.

The findings of the current study have potential important implications for a wide range of parties who use the information provided by CRAs. These include (Boot et al., 2006) : issuers of debt (in this context, banks) who request a rating; investors purchasing short- or long-term debt ('buy-side' participants); investment banks marketing debt securities ('sell-side' participants); trade and commodity financiers assessing risk in individual transactions; and regulators, assessing the credit risk associated with an institution's assets and liabilities. The House of Commons' report (May 2009) indicates that market participants seemed to over-rely on these ratings. In this context, the findings of the current study indicate that banks' credit ratings did not pick up major risks such as lack of liquidity and capital adequacy. In addition, under the Basel II agreement, banks can use ratings from approved credit rating agencies such as Standard & Poor's when calculating their net capital reserve regulatory requirements. However, if banks' credit ratings do not in fact reflect this risk, a change in regulation might be necessary, with reduced reliance on ratings agencies and even on risk weighting, in the policy framework.

References

Adams, M., Burton, B., and Hardwick, P. 2003. The Determinants of Credit Ratings in the United Kingdom Insurance Industry. Journal of Business Finance & Accounting 30 (3-4), 539-572.

Afonso, A. 2003. Understanding the determinants of sovereign debt ratings: Evidence for the two leading agencies. Journal of Economics and Finance 27(1), 56-74.

Ahn, H., and Kim, K. 2009. Bankruptcy prediction modelling with hybrid case-based reasoning and genetic algorithms approach. Applied Soft Computing 9 (2), 599-607.Altman, E. I., and Rijken, H. A., 2004. How rating agencies achieve rating stability. Journal of Banking and Finance 28, 2679–714.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance 23 (4), 589–609.

Altman, E.I., and Saunders, A. 2001. An analysis and critique of the BIS proposal on capital adequacy and ratings, Journal of Banking & Finance 25 (1), 25–46.

Altman, E.I., Haldeman, R.G., and Narayanan, P., 1977. Zeta analysis: a new model to identify bankruptcy risk of corporations. Journal of Banking and Finance 1 (1), 29–54.

Amato, J.D., and Furfine, C.H. 2004. Are Credit Ratings Procyclical? Journal of Banking and Finance 28 (11), 2641–2677.

Ashbaugh-Skaife, H., Collins, D.W., and LaFond, R., 2006. The effect of corporate governance on firms' credit ratings. Journal of Accounting and Economics 42, 203–243.

Barrell R, Davis, E. P., Karim, D., and Liadze I., 2010. Bank regulation, property prices and early warning systems for banking crises in OECD countries. Journal of Banking and Finance 34, 2255–2264.

Bellotti, T., Matousek, R., and Stewart, C. 2011a. A note comparing support vector machines and ordered choice models' predictions of international banks' rating. Decision Support Systems 51(3), June, 682-687.

Bellotti, T., Matousek, R., and Stewart, C. 2011b. Are rating agencies' assignments opaque? Evidence from international banks. Expert Systems with Applications 38(4), April, 4206-4214.

Bennell, J. A., Crabbe, D., Thomas S., and Gwilym, O. 2006. Modelling sovereign credit ratings: Neural networks versus ordered probit. Expert Systems with Applications 30(3), April, 415–425.

Bissoondoyal-Bheenick, E . 2005. An analysis of the determinants of sovereign ratings. Global Finance Journal 15: 251–280.

Bissoondoyal-Bheenick, E. and Treepongkaruna, S. 2011. An analysis of the determinants of bank ratings: comparison across ratings agencies. Australian Journal of Management 36(3), 405 –424.

Blume, M.E., Lim, F., and Mackinlay, A.C., 1998. The declining credit quality of U.S. corporate debt: myth or reality? The Journal of Finance 53(4), 1389-1413.

Bonfim , D. 2009. Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics , Journal of Banking & Finance 33(2), 281-299.

Boot, A.W.A., Milbourn, T.T., and Schmeits, A., 2006. Credit ratings as coordination mechanisms. Review of Financial Studies 19, 81–118.

Brotman, B.A. 1989. Reliability of Best's Insurer Ratings Using Financial Information Published in the Annual *Report.* Journal of Insurance Issues and Practices 12, 58-70.

Cantor, R., and Packer, F. 1996. Determinants and Impact of Sovereign Credit Ratings. Economic Policy Review_2(2), October, 37-54.

Chami, R., and Cosimano, T. 2003.The nature of capital adequacy constraints under the Basel accord., mimeo, IMF Institute.

Chaudhuri, A., and De, K. 2011. Fuzzy Support Vector Machine for bankruptcy prediction. Applied Soft Computing 11 (2), 2472-2486.

Cheng, M., and Neamtiu, M. 2009. An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility. Journal of Accounting and Economics 47(1-2), 108-130.

Demsetz, R.S., and Strahan, P.E., 1997.Diversification, Size, and Risk at Bank Holding Companies., Journal of Money, Credit, and Banking 29, 300-313.

Duff, A., and Einig, S., 2009a. Credit ratings quality: The perceptions of market participants and other interested parties. The British Accounting Review 41 (3), 141–153.

Duff, A., and Einig, S. 2009b. Understanding credit ratings quality: Evidence from UK debt market participants. The British Accounting Review 41 (2), 107-119.

Evanoff, D., and Wall, L. D., 2000. Subordinated debt and bank capital reform. Federal Reserve Bank of Chicago, Economic Perspective 24, 40-53.

Frost, C.A., 2007. Credit rating agencies in capital markets: a review of research evidence on selected criticisms of the agencies. Journal of Accounting, Auditing & Finance 22 (3), p469-492.

Gray, S., Mirkovic, A., and Ragunathan, V. 2006. The determinants of credit ratings: Australian evidence. Australian Journal of Management. Vol. 31 (2), 333-354.

Haldane, A., and Madouros, V., 2012.The dog and the Frisbee. bankofengland.co.uk/publications/Pages/speeches/2012/596.aspx

Hand, J., Holthausen, R., and Leftwich, R.,1992. The effect of bond rating announcements on bond and stock prices. Journal of Finance 47(2), 733-752.

Holthausen, R., and Leftwich, R. 1986. The effect of bond rating changes on common stock prices. Journal of Financial Economics 17 (1), 57-90.

House of Commons, 2009. Banking Crisis: reforming corporate governance and pay in the City - Treasury Contents. Treasury Committee Publications, Last accessed on the 3rd of August, 2010. http://www.publications.parliament.uk/pa/cm200809/cmselect/cmtreasy/519/51908.htm#n294

Iannotta, G. 2006. Testing for opaqueness in the European banking industry: evidence from bond credit ratings, Journal of Financial Services Research 30 (3), 287–309.

Iskandar-Datta, M.E., and Emery, D. R. 1994. An empirical investigation of the role of indenture provisions in determining bond ratings. Journal of Banking & Finance 18 (1), 93-111.

Kaplan, R., and Urwitz, G. 1979. Statistical models of bond ratings: a methodological inquiry. Journal of Business 52 (2l), 231-161.

Levonian, M.2001.Subordinated debt and the quality of Market discipline in banking. Federal Reserve of San Francisco, mimeo.

Liao, H., Chen, T., and Lu, C. 2009. Bank credit risk and structural credit models: Agency and information asymmetry perspectives . Journal of Banking & Finance 33(8), 1520-1530.

Molinero, C.M., Gomez, P.A., and Cinca, C.S. 1996. A multivariate study of Spanish bond ratings. Omega 24(4), 451-462.

Merton, R. 1977.An Analytical Derivation of the Cost of Deposit Insurance and Loan Guarantees. Journal of Banking and Finance 1, 3-11.

Öğüt, H., Doğanay, M. M., Ceylan, N.B. and Aktaş, R. 2012. Prediction of bank financial strength ratings: The case of Turkey. Economic Modelling 29, 632–640.

Packer, F. and Tarashev, N. 2011. Rating methodologies for banks, BIS Quarterly Review, (June), 39-52.

Poon, W. P.H., Firth, M., and Fung, H. 1999. A multivariate analysis of the determinants of Moody's bank financial strength ratings. Journal of International Financial Markets, Institutions and Money 9(3), 267-283.

Pottier, S.W. 1997. Life Insurer Risk Characteristics and the Rating Process. The Journal of Insurance Issues 20, 111-130.

Pottier, S.W. 1998. Life Insurer Financial Distress, Best's Ratings and Financial Ratios. The Journal of Risk and Insurance 65, 275-288.

Shen, C., Huang, Y., and Hasan, I. 2012. Asymmetric benchmarking in bank credit rating. Journal of International Financial Markets, Institutions & Money 22, 171– 193.

Shin, K., and Lee, Y. 2002. A genetic algorithm application in bankruptcy prediction modelling. Expert Systems with Applications 23(3), 321-328. Weber, J. 2006. Discussion of the effects of corporate governance on firms' credit ratings. Journal of Accounting and Economics 42, 245-254.

Zhu, Haibin (2008). "Capital regulation and banks' financial decisions". *International Journal of Central Banking*, March 2008.

Tables

Table (1) Results for the principle component analysis

	Size		Leverage		Profitability		Efficiency		Liquidity		Risk		Capital adequacy	
Variable	PC 1	PC 2	PC 1	PC 2	PC 1	PC 2	PC 1	PC 2	PC 1	PC 2	PC 1	PC 2	PC 1	PC 2
1	0.69	0.09	0.52	-0.46	0.47	-0.13	0.12	0.95	0.47	-0.03	0.49	-0.45	0.49	-0.03
2	0.64	0.25	0.18	-0.05	0.52	0.03	0.49	-0.31	-0.40	0.48	0.42	0.48	0.49	0.02
3	0.34	-0.55	0.54	-0.45	0.34	0.77	0.59	0.00	0.31	0.63	0.62	-0.04	0.50	0.07
4	-0.02	-0.34	0.48	0.52	0.51	0.02	0.63	0.05	0.39	0.45	-0.45	-0.12	0.48	0.22
5	-0.07	0.71	0.43	0.57	0.37	-0.62			0.46	0.00	-0.02	0.74	-0.02	0.73
6									-0.41	0.40			-0.18	0.64
Cumulative Proportion	0.34	0.61	0.44	0.79	0.73	0.89	0.61	0.86	0.70	0.90	0.41	0.73	0.58	0.78

Table 2: Variables definition

Variable	Definition	Expected relationship
	Credit ratings	
RT6FOR	Forward-looking credit rating that takes place 6 months prior to the financial year-end	
RT12BK	Backward-looking Credit rating that takes place within 12 months after the financial year-end	
	Bank Size	
Asset1	The natural logarithm of a three-year arithmetic average of total assets	+
Asset5	A three-year arithmetic average of total assets deflated by a three-year arithmetic average of business volume	+
	Leverage	
LEV3	A three-year arithmetic average of the ratio (total long term funding minus total equity all deflated by total assets)	-
LEV5	Average Interest-Bearing Liabilities divided by Average Earning Assets	-
	Profitability	
Profit2	A three-year arithmetic average of net interest margin. This ratio is the net interest income expressed as a percentage of earning assets.	+
Profit3	A three-year arithmetic average of the ratio net interest income less loan impairment charges all deflated by average earning assets.	+
	Efficiency	
EFF1	A three-year arithmetic average of the ratio cost to income	-
EFF4	A three-year arithmetic average of the ratio non-interest expenses to average assets	-
	Liquidity	
LIQ1	A three-year arithmetic average of the ratio net loans to total assets	-
LIQ3	A three-year arithmetic average of the ratio Loans to Customer Deposits	-

Risk (asset quality)		
Risk3	A three-year arithmetic average of the ratio net charge off or the amount written-off from loan loss reserves less recoveries to gross loans	-
Risk5	A three-year arithmetic average of growth of gross loans of a bank deflated by total growth of gross loans of the sample banks	-
Capital adequacy		
CAP3	A three-year arithmetic average of the ratio equity / total assets	+
CAP5	A three-year arithmetic average of the ratio subordinated borrowing to total assets	-

Table (3) Descriptive analysis:

Panel A: Frequency of ratings:

Rating category	RT12BK	RT6FOR
1	88	81
2	264	262
3	51	58
Total	403	401

Panel B: RT12BK : Backward-looking credit ratings

Rated [AAA; AA]						
	Minimum	Maximum	Mean	STD	Skewness	Kurtosis
Assets1 [mil USD]	605	1993529	447,834	562940	1.30	0.80
Assets5	0.61	1.00	0.85	0.11	-0.21	-0.86
LEV3	0.00	0.31	0.09	0.08	0.88	0.51
LEV5	0.02	1.37	0.64	0.25	0.35	0.65
Profit2	0.08	5.88	2.28	1.68	1.05	-0.26
Profit3	0.40	5.63	2.07	1.80	0.96	-0.72
EFF4	0.12	4.58	2.26	1.19	0.54	-0.70
EFF1	11.86	82.57	55.45	13.99	-0.90	2.02
LIQ1	1.74	96.80	54.06	20.16	-0.26	0.47
LIQ3	75.47	497.00	143.64	96.58	3.02	9.21
Risk3	0.07	0.94	0.44	0.21	0.43	0.13
Risk5	0.00	0.00	0.00	0.00	0.14	-0.18
CAP3	1.62	79.48	10.62	16.87	3.12	9.65
CAP5	0.00	0.04	0.02	0.01	0.46	-0.54
RATED [AA-; A+; A]						
Assets1[mil USD]	258	2540774	103,723	359072	5.49	31.79
Assets5	0.08	1.00	0.72	0.24	-1.22	0.90
LEV3	0.00	0.90	0.07	0.12	3.38	15.69
LEV5	0.00	1.24	0.73	0.29	-1.10	0.76
Profit2	-0.46	14.26	3.70	2.27	1.36	3.94
Profit3	-0.53	11.40	3.12	1.77	0.91	3.48
EFF4	0.09	41.34	4.40	5.27	3.45	16.32
EFF1	3.24	109.75	56.14	17.98	-0.42	1.75
LIQ1	0.00	95.90	62.72	22.47	-1.36	1.58
LIQ3	0.00	513.20	125.34	82.39	2.25	7.01

Risk3	-5.13	6.06	0.80	1.40	1.67	5.85
Risk5	0.00	0.02	0.00	0.00	2.85	11.86
CAP3	1.43	95.05	11.36	11.56	3.87	19.39
CAP5	0.00	0.22	0.02	0.03	4.61	25.68
RATED [A-; BBB+; BBB; BBB-]						
Assets1[mil USD]	353	185767	15,617	29656	4.51	22.42
Assets5	0.08	1.00	0.70	0.29	-1.07	-0.31
LEV3	0.00	0.61	0.07	0.13	2.82	7.92
LEV5	0.07	1.07	0.71	0.20	-0.65	0.48
Profit2	0.54	9.24	3.51	1.80	0.75	1.35
Profit3	0.15	5.29	2.73	1.31	-0.33	-0.67
EFF4	-1.29	20.49	4.74	4.44	1.51	2.16
EFF1	13.68	153.06	67.12	21.20	0.57	4.79
LIQ1	23.00	89.27	63.79	16.22	-0.36	-0.31
LIQ3	47.81	493.00	117.03	67.27	3.65	17.55
Risk3	-0.10	6.89	1.05	1.63	2.00	3.47
Risk5	0.00	0.01	0.00	0.00	1.04	2.06
CAP3	2.52	67.65	13.83	12.27	2.94	9.30
CAP5	0.00	0.05	0.01	0.01	1.21	0.99

Panel C: RT6FOR :Forward-looking credit ratings

Rated [AAA; AA]

	Minimum	Maximum	Mean	STD	Skewness	Kurtosis
Assets1[mil USD]	258	2448493	512,110	671268	1.40	1.13
Assets5	0.61	1.00	0.84	0.11	-0.02	-0.78
LEV3	0.00	0.29	0.08	0.07	0.90	0.38
LEV5	0.02	1.09	0.65	0.24	-0.12	-0.43
Profit2	0.17	6.14	2.53	1.82	0.86	-0.86
Profit3	0.40	5.63	2.14	1.83	0.85	-1.04
EFF4	0.22	5.17	2.48	1.32	0.57	-0.85
EFF1	9.97	82.57	56.68	13.52	-1.18	2.82
LIQ1	1.93	96.80	54.15	19.27	-0.50	0.14
LIQ3	75.80	459.90	130.95	66.45	3.67	17.34
Risk3	0.04	1.52	0.52	0.27	1.35	4.32
Risk5	0.00	0.01	0.00	0.00	-0.53	2.36
CAP3	1.87	95.05	11.92	20.15	3.11	9.30
CAP5	0.00	0.04	0.02	0.01	0.37	-0.55
RATED [AA-; A+; A]						
Assets1[mil USD]	614	2540774	78,694	282414	6.96	54.44
Assets5	0.08	1.00	0.70	0.25	-1.07	0.30
LEV3	0.00	0.90	0.08	0.13	3.17	13.47
LEV5	0.00	1.22	0.71	0.29	-1.08	0.64
Profit2	-0.46	14.26	3.85	2.34	1.36	3.54
Profit3	-0.53	11.40	3.12	1.77	1.00	3.91
EFF4	0.04	31.83	4.69	4.99	2.32	6.40
EFF1	1.97	105.86	55.97	17.41	-0.58	1.83
LIQ1	0.00	96.26	62.81	22.86	-1.38	1.62
LIQ3	0.00	511.23	128.55	90.09	2.12	5.71

Risk3	-5.13	6.89	1.03	1.66	1.43	3.31
Risk5	-0.01	0.02	0.00	0.00	2.44	10.40
CAP3	1.43	72.99	11.90	10.77	3.15	12.52
CAP5	0.00	0.22	0.02	0.04	4.21	20.06
RATED [A-; BBB+; BBB; BBB-]						
Assets1[mil USD]	377	188441	13,959	26516	5.82	38.24
Assets5	0.09	1.00	0.72	0.28	-1.19	0.07
LEV3	0.00	0.58	0.07	0.12	2.83	8.31
LEV5	0.07	1.01	0.71	0.20	-0.74	0.38
Profit2	0.49	6.85	3.13	1.60	0.11	-0.26
Profit3	0.07	5.36	2.70	1.33	-0.39	-0.65
EFF4	-1.29	13.10	3.97	3.62	1.17	0.54
EFF1	13.68	153.06	69.71	22.46	0.40	4.18
LIQ1	23.00	89.27	62.18	16.85	-0.31	-0.55
LIQ3	39.24	513.20	115.87	71.66	3.96	20.20
Risk3	-0.10	4.13	0.69	1.12	2.17	3.72
Risk5	0.00	0.01	0.00	0.00	0.99	2.39
CAP3	2.09	67.65	12.90	12.86	3.09	9.86
CAP5	0.00	0.05	0.01	0.01	1.22	1.29

Table (4) Correlations results (*Values in parentheses are probabilities of significance)*

	RT12BK	RT6FOR	ASSETS1	ASSETS5	LEV3	LEVE5	PROFIT2	PROFIT3	EFF4	EFF1	LIQ1	LIQ3	RISK3	RISK5	CAP3	CAP5
RT12BK	1.000															
	(-----)															
RT6FOR	0.792	1.000														
	(0.000)	(-----)														
ASSETS1	0.395	0.454	1.000													
	(0.000)	(0.000)	(-----)													
ASSETS5	0.306	0.237	0.094	1.000												
	(0.000)	(0.001)	(0.202)	(-----)												
LEV3	0.083	0.064	0.391	-0.039	1.000											
	(0.261)	(0.385)	(0.000)	(0.604)	(-----)											
LEV5	-0.137	-0.205	-0.205	-0.142	0.099	1.000										
	(0.064)	(0.005)	(0.005)	(0.055)	(0.181)	(-----)										
PROFIT2	-0.207	-0.166	-0.352	-0.606	0.013	0.333	1.000									
	(0.005)	(0.025)	(0.000)	(0.000)	(0.861)	(0.000)	(-----)									
PROFIT3	-0.059	-0.153	-0.496	-0.252	-0.225	0.337	0.809	1.000								
	(0.424)	(0.038)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(-----)								
EFF4	-0.289	-0.190	-0.170	-0.812	0.198	0.017	0.708	0.317	1.000							
	(0.000)	(0.010)	(0.021)	(0.000)	(0.007)	(0.815)	(0.000)	(0.000)	(-----)							

EFF1	-0.195	-0.165	-0.055	0.070	-0.115	-0.278	-0.157	-0.106	0.122	1.000						
	(0.008)	(0.025)	(0.457)	(0.348)	(0.121)	(0.000)	(0.034)	(0.151)	(0.099)	(-----)						
LIQ1	-0.148	-0.199	-0.184	-0.153	0.225	0.879	0.384	0.273	0.091	-0.316	1.000					
	(0.044)	(0.007)	(0.013)	(0.038)	(0.002)	(0.000)	(0.000)	(0.000)	(0.221)	(0.000)	(-----)					
LIQ3	0.161	0.112	0.207	-0.080	0.608	0.424	0.184	0.023	0.149	-0.310	0.546	1.000				
	(0.029)	(0.130)	(0.005)	(0.281)	(0.000)	(0.000)	(0.013)	(0.757)	(0.043)	(0.000)	(0.000)	(-----)				
RISK3	-0.225	-0.050	0.054	-0.633	0.263	0.029	0.540	0.032	0.703	-0.081	0.166	0.216	1.000			
	(0.002)	(0.504)	(0.467)	(0.000)	(0.000)	(0.696)	(0.000)	(0.662)	(0.000)	(0.276)	(0.024)	(0.003)	(-----)			
RISK5	0.116	0.089	0.153	-0.021	0.128	0.176	-0.121	-0.048	0.017	-0.207	-0.054	0.118	-0.078	1.000		
	(0.116)	(0.230)	(0.038)	(0.775)	(0.084)	(0.017)	(0.102)	(0.520)	(0.815)	(0.005)	(0.468)	(0.111)	(0.292)	(-----)		
CAP3	-0.228	-0.182	-0.401	-0.403	-0.219	0.101	0.244	0.187	0.370	-0.170	-0.074	-0.138	0.166	0.340	1.000	
	(0.002)	(0.013)	(0.000)	(0.000)	(0.003)	(0.171)	(0.001)	(0.011)	(0.000)	(0.021)	(0.318)	(0.062)	(0.024)	(0.000)	(-----)	
CAP5	0.125	0.131	0.259	-0.026	-0.135	-0.040	-0.335	-0.298	-0.266	-0.138	-0.149	-0.128	-0.175	0.045	0.068	1.000
	(0.092)	(0.076)	(0.000)	(0.726)	(0.068)	(0.586)	(0.000)	(0.000)	(0.000)	(0.061)	(0.043)	(0.082)	(0.018)	(0.548)	(0.357)	(-----)

Table (5) Ordered logit regression results for the period 1994-2009

Dependent Var.		RT12BK		RT6FOR	
		Max	Min	Max	Min
Assets1	+	0.740***	0.614***	0.724***	0.699***
		(0.000)	(0.000)	(0.000)	(0.000)
Assets5	+	3.902**		5.575***	
		(0.022)		(0.001)	
LEV3	-	-4.830	0.349	-7.152***	-0.988
		(0.100)	(0.832)	(0.009)	(0.562)
LEV5	-	-0.563		-0.403	
		(0.831)		(0.875)	
Profit2	+	-1.319***	0.355***	-0.103	0.335***
		(0.008)	(0.011)	(0.816)	(0.013)
Profit3	+	1.478***		0.317	
		(0.001)		(0.414)	
EFF4	-	0.342**	-0.161**	0.211	-0.152**
		(0.028)	(0.017)	(0.151)	(0.030)
EFF1	-	-0.078***		-0.055***	
		(0.000)		(0.004)	
LIQ1	-	-0.021	-0.022*	-0.033	-0.028**
		(0.551)	(0.079)	(0.345)	(0.024)
LIQ3	-	0.009**		0.007**	
		(0.015)		(0.049)	
Risk3	-	0.223	-0.165	0.160	0.053
		(0.493)	(0.299)	(0.591)	(0.739)

Risk5	-	-77.867		-0.773	
		(0.516)		(0.995)	
CAP3	+	-0.056	-0.019	-0.014	-0.012
		(0.269)	(0.431)	(0.787)	(0.619)
CAP5	-	7.387		11.917	
		(0.580)		(0.376)	
Pseudo R-squared		0.297	0.176	0.265	0.2017
Akaike info criterion		1.339	1.468	1.448	1.4706
N		198	221	188	210
Dep. Value		% Correct	% Correct	% Correct	% Correct
1		57.14	11.36	44.12	13.89
2		89.55	92.00	88.80	92.14
3		36.36	25.93	44.83	50.00
Total		76.77	67.87	73.94	71.91

Values in parentheses are probabilities of significance. * ** Significant at 1% level (two-tailed). ** Significant at 5% level (two-tailed). * Significant at 10% level (two-tailed).

Table (6) Ordered logit regression results for the period 2002-2009

Dependent Var.		RT12BK		RT6FOR	
		Max	Min	Max	Min
Assets1	+	0.891***	0.792***	1.044***	0.876***
		(0.000)	(0.000)	(0.000)	(0.000)
Assets5	+	3.194		6.207**	
		(0.238)		(0.027)	
LEV3	-	-1.066	1.579	-5.707	0.454
		(0.771)	(0.344)	(0.116)	(0.805)
LEV5	-	-0.635		-4.184	
		(0.851)		(0.269)	
Profit2	+	-2.947***	0.242	-2.073*	0.195
		(0.012)	(0.141)	(0.075)	(0.265)
Profit3	+	2.476**		1.598	
		(0.021)		(0.129)	
EFF4	-	0.432	-0.175*	0.401	-0.248**
		(0.112)	(0.085)	(0.137)	(0.020)
EFF1	-	-0.085***		-0.070***	
		(0.001)		(0.007)	
LIQ1	-	-0.023	-0.008	-0.017	-0.019
		(0.617)	(0.599)	(0.729)	(0.270)
LIQ3	-	0.017***		0.020***	
		(0.013)		(0.003)	
Risk3	-	1.342	-0.103	1.441	0.506*
		(0.219)	(0.716)	(0.207)	(0.081)
Risk5	-	-130.077		32.584	

		0.437		0.846	
CAP3	+	0.077	0.009	0.179**	0.009
		(0.283)	(0.754)	(0.037)	(0.766)
CAP5	-	-18.543		-19.615	
		(0.338)		(0.336)	
Pseudo R-squared		0.429	0.282	0.481	0.343
Akaike info criterion		1.355	1.532	1.305	1.450
N		120	135	113	127
Dep. Value		% Correct	% Correct	% Correct	% Correct
1		82.05	53.66	70.00	50.00
2		80.30	75.68	82.54	80.00
3		53.33	35.00	65.00	76.00
Total		77.50	62.96	76.11	71.65

Values in parentheses are probabilities of significance. * ** Significant at 1% level (two-tailed). ** Significant at 5% level (two-tailed). * Significant at 10% level (two-tailed).

Table (7) The P-values results of Wald test

	Full sample		Shorter sample	
	RT12BK	**RT6FOR**	**RT12BK**	**RT6FOR**
MIN. Model	C(3)= C(11)= C(13)=0		c(3)=c(5)=c(9)=c(13)=0	
F-statistic	(0.543)	(0.894)	(0.545)	(0.717)
Chi-square	(0.542)	(0.894)	(0.542)	(0.717)
MAX. Model	c(4)= c(9)= c(11)= c(12)= c(13)= c(14)=0		c(3)=c(4)=c(7)=c(9)=c(11)=c(12)=c(14)=0	
F-statistic	NA	(0.360)	(0.176)	(0.027)**
Chi-square	NA	(0.355)	(0.176)	(0.019)**

Values in parentheses are probabilities of significance. * ** Significant at 1% level (two-tailed). ** Significant at 5% level (two-tailed). For presentation purposes: C1: ASSETS1; C2: ASSETS5; C3: LEV3; C4:LEVE5; C5: PROFIT2; C6: PROFIT3; C7:EFF4; C8:EFF1; C9:LIQ1; C10:LIQ3; C11:RISK3; C12:RISK5; C13:CAP3; C14:CAP5.