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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

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.

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 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 fina 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 empha 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.

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 failu 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).

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 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

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 summa

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*

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 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

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

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Tables

	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
	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
	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
	0.34	-0.55	0.54	-0.45	0.34	0.77								

[redacted]

[redacted]	
[redacted]	-
[redacted]	-
[redacted]	
[redacted]	+

[redacted]

[redacted]

Panel B: RT12BK : Backward-looking credit ratings

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

Panel C: RT6FOR :Forward-looking credit ratings

	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				

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
-	-					
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	-				r	

	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 0.20565.2(.064)5.2())]TJ/TT51Tf2.880288028802880288028802880288028802880288028802880288028802880288028802880288028802880288028802880288028802880288023620(8802880288016288
006 Tc [(0.0)4.4(9)-1.5(9)]TJ 4.2575 02TD [(1.0)4.3.9881TD 0 Tc <0003>Tj /T-19.193TD 2.5764 Tc -.0131 Tc [(.85.3(0)-5.2(.8 0 TD -90421 Tc [(()-5.3(0)-5.2(.005)-5.329 Tc /TT8 1 Tf 2.21566.2

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)	(-----)

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

	-	-77.867		-0.773	
		(0.516)		(0.995)	
	+	-0.056	-0.019	-0.014	-0.012
		(0.269)	(0.431)	(0.787)	(0.619)
	-	7.387		11.917	
		(0.580)		(0.376)	
-		0.297	0.176	0.265	0.2017
		1.339	1.468	1.448	1.4706
		198	221	188	210

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

		0.437		0.846	
	+	0.077	0.009	0.179**	0.009
		(0.283)	(0.754)	(0.037)	(0.766)
	-	-18.543		-19.615	
		(0.338)		(0.336)	
-		0.429	0.282	0.481	0.343
		1.355	1.532		

Table (7) The P-values results