# Determinants of Banks' Credit Ratings: Evidence from Jordan

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## ABSTRACT

This study investigates the factors that affect Moody's credit ratings of commercial banks using an ordered probit model. We propose an empirical model designed to forecast bank credit ratings using quantitative publicly available information from their financial statements. The sample consists of 13 Jordanian commercial banks over the period (2000-2013). The study estimates a forecasted credit rating of the banks investigated based on the proposed model. The results show that profitability ratios, asset quality ratios, liquidity ratios, capital adequacy ratios and the size of the bank have statistically significant effects on the banks credit ratings.These results have important implications to banks' customers, investors, management and the regulatory authority.

**Keywords**: Credit Rating, Jordanian Commercial Banks, Ordered Probit Model, Amman Stock Exchange.

## INTRODUCTION

Credit rating agencies have been around for the better part of the 20th century. Credit rating agencies (CRAs) give a rating scale of risks associated with the ability of banks to meet debt obligations on time. These ratings are used by investors, borrowers, issuers and governments in making investment and financial decisions. Consequently, changes in ratings lead to important changes in capital allocation(Gogas*et al*., 2014). The three major rating agencies worldwide are Standard & Poor's (established in 1906), Moody's (established in 1909) and Fitch (established in 1913).

The implementation of Basel II strengthened the demand for ratings and expanded the role of the CRAs. Also in 1988, the Basel Committee proposed the CAMEL framework for assessing financial institutions, based on the evaluation of five critical elements of a financial institution's operations: Capital adequacy, Asset quality, Management soundness, Earnings and profitability, and Liquidity (Dash and Das, 2013). In 1997, a sixth component has been added, Sensitivity to market risk, in order to form the CAMELS framework (Gilbert *et al*., 2000).

Under the CAMELS framework, financial institutions are required to enhance capital adequacy, strengthen asset quality, improve management, increase earnings, maintain liquidity, and reduce sensitivity to various financial risks. The rating agencies play an important role in the pricing of credit risk. However, their straightness has been under consideration due to cases such as Enron (USA, 2001) and Lehman Brothers (USA, 2008) which had been assessed, by the rating agencies, with high ratings just a few days before their collapses. For this reason, they are often blamed for not being able to provide the market with the appropriate ratings required for important investment decisions. Such cases also occurred during the global financial crisis of 2008 and turn the interest in credit rating methodologies. It is generally accepted that when the

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credit rating of a bank is downgraded from the CRAs then things get worse for the specific banking institution and vice versa (Gogas*et al*.,2014).

Rating agencies have established themselves internationally and they are viewed as being more credible than domestic rating agencies in most countries. Credit ratings that are paid for and initiated by issuers are commonly known as solicited ratings. There are numerous advantages of credit rating agencies, first**,** they help good institutions get better rates**;** institutions with higher grade credit ratings are able to borrow money at more favorable interest rates (Hamarneh, 2014). Accordingly, this rewards organizations that are responsible about managing their money and paying off their debt. In turn, they will be able to expand their business at a faster rate, which helps stimulate the economy's expansion as well**.** Second**,** they warn investors of risky companies. Third, they provide a fair risk-returnratio**,** not all investors are opposed to buying risky debt securities. However, they want to know that they are going to be rewarded if they take on a high level of risk. For this reason, credit rating agencies will inform them of the risk levels for every debt instrument and help ensure that they are properly compensated for the level of risk they take on**.** Finally they give institutions an incentive to improve, thus, a poor credit rating can be a wake-up call for institutions that have taken on too much debt or have not demonstrated that they are willing to be responsible about paying it back. These institutions are often in denial of their credit problems, and need to be alerted of any potential problems from an analyst before they make the necessary changes**.** However, there are disadvantages of credit rating agencies, likeevaluation is sometimes highly subjective, there can be conflict of interests, and ratings are not always accurate.

Overall, credit rating is a vital issue that concerns investors in order to take the right decision to invest or not, depositors to increase their confidence in the banks they deal with, managers to enhance the performance of those banks which they operate and the regulatory body specifically the central bank to insure the creditability of the banking system. This study has three main objectives: the first is to investigate the determinants of Moody's credit ratings of Jordanian commercial banks, the second is to propose a model for forecasting banks' credit ratings and the third is to forecast credit ratings for Jordanian commercial banks over the period (2000-2013).The importance of this study comes as being (to the best of authors' knowledge) the first study in Jordan that executes a credit rating for the commercial banks over a relatively this long period of time. Moreover, the importance of this study is that it is the first one in Jordan that determines the factors that affect the banks credit ratings, and specifically Moody's credit ratings of Jordanian commercial banks. It proposes an empirical model designed to forecast bank credit ratings using only quantitative and publicly available information from their financial statements. Forecasting credit rating of the banking system in a developing country like Jordan is very critical. Thus, credit ratings represent direct indicators of the solidity and stability of the banking system which plays a very essential role in the Jordanian economy. It pledges stability and facilitates economic growth. Banks also play a central role in the money creation process and in the payment system. In addition, the intermediation role that banks execute between savers and borrowers facilitate credit to finance personal and commercial needs of funding which in turn move the economic cycle and promote investments.The remaining of the study is organized as follows: Section 2 reviews the related literature. Section 3 describes data and methodology. Section 4 reports the results of analysis and Section 5 concludes.

## 2. Literature review

Early studies use different methodologies to forecast credit ratings. Some of them use logistic regressions and multivariate discriminant analysis; see for example, (Pinches and Mingo, 1973;Belkaoui, 1980; Ederington, 1985). Others depend on more advanced techniques such as neural networks (Surkan and Singleton, 1990; Kim et al.,1993; Moody and Utans, 1994; Maher and Sen, 1997). Several recent studies have investigated the determinants of credit ratings around the world.Gray *et al.* (2006) examine the effect that various industry and financial variables have on credit ratings issued for Australian firms by Standard and Poor's. The ordered probit model indicates that leverage ratios and interest coverage have the most pronounced effect on credit ratings. Industry concentration measures and profitability variables were also important. They also document a consistent trend towards lower ratings. These results serve to corroborate similar evidence from U.S. markets presented by Blume, *et al*. (1998). Financial variables are helpful in discriminating between A- and BBB-rated firms, but are less precise in separating AA- and A-rated firms.

Pasiouras,*et al.* (2007) investigate whether it is possible to develop a multicriteria decision model to replicate the credit ratings of Fitch on Asian banks. The ratings correspond to October 2004, while the financial data correspond to end 2003. Following a tenfold cross validation procedure, the model was developed with the Multi-group Hierarchical Discrimination (MHDIS) approach .Five financial variables were selected from a list of 19 ones through factor analysis. Also an additional set of five non-financial variables covering corporate governance, ownership, strength of bank's franchise,auditing and its banking environment was being used. The results reveal that equity to customer and short term funding (EQFUND), return on average equity (ROAE) and net interest margin (NIM) are the most important financial variables. The number of subsidiaries, the number of shareholders and the banking environment of the country where the banks operate are the most important non-financial ones. Also, the results show that the MHDIS model can replicate the credit ratings of Fitch with a satisfactory accuracy and is more efficient than discriminate analysis and ordered logistic regression that are used for comparison objectives.

Shiu and Chiang (2008) investigate the relationship between the financial strength ratings of Lloyd's syndicate and their determinants. Lloyd's market plays an important role in the global insurance business. Using the Lloyd's market data on syndicates financial strength ratings and their financial information for the period from 2004 through 2007, they examine the determinants of the syndicates letter ratings assigned by Standard & Poor's. An ordered probit regression is utilized to carry out the empirical analysis. The results show that concentration index, leverage, and reinsurance are negatively related to financial strength ratings, while profit, liquidity, growth rate and size have a positive impact on the ratings.

Afonso,*et al.* (2009) compare three procedures to estimate the determinants of sovereign ratings under an ordered response framework: ordered probit, ordered logit and random effects ordered probit, their panel data set includes information on rating notations for two of the main ratingagencies (Standard and Poor's and Moody's), covering 66 countries between 1996 and 2005. Of the three procedures, the study finds that the most efficient method is the random effects ordered probit estimation.

Bheenick and Treepongkaruna (2011) test the quantitative determinants of bank ratings, provided by Standard & Poor's, Moody's, and Fitch in the United Kingdom and Australia. The ratings used in this study are for the period 2006–2009.The final sample of commercial banks for which ratings across the ratings agencies were available includes 20 commercial banks from Australia and 49 others from the UK. The main finding is that the quantitative factors that reflect asset quality, liquidity risk, operating performance and capital adequacy are the key determinants of bank ratings across the rating agencies. However, macroeconomic variables and market risk factors do not seem to be contributing factors in explaining bank ratings in either countries.

Chen (2012) analyzes the determinants of credit ratings, classify credit ratings and provide meaningful decision rules for interested parties, this study proposes an integrated procedure.The experimental focus is the Asian banking industry. Asia is at the front of global economic growth, even though its investment environment is very risky and uncertain. Data were restored from BankScope[1]database that covers 1327 Asian banks over the period 1993–2007 .This study adopts an integrated feature-selection approach to select key attributes, and then adopts an objective cumulative probability distribution approach (CPDA) to partition selected condition attributes by applying rough sets local-discretization cuts. This paper then applies the rough sets LEM2 algorithm to generate a comprehensible set of decision rules. Finally, this paper utilizes a rule filter to eliminate rules with poor support and thereby improves rule quality. Experimental results demonstrate that the proposed procedure is an effective method of removing irrelevant attributes and achieving increased accuracy, providing a knowledge-based system for classification of rules and for solving credit-rating problems encountered by banks, thereby benefiting interested parties.

Chen and Cheng (2013) argue that issuers and investors need a credit rating indicator to help them identifying the financial status and the competence of banks. A credit rating provides financial entities with an evaluation of credit worthiness, default probability, and investment risk. Although numerous models have been proposed to solve credit rating problems, they have drawbacks for example, lack of explanatory power; numerous variables, which result in multiple dimensions and complex data; and reliance on the restrictive assumptions of statistical techniques. To overcome these shortcomings, this study applies two hybrid models that solve the practical problems in credit rating classification. For model verification, this study uses an experimental dataset collected from the Bankscope database over the period 1998–2007. Experimental results demonstrate that the proposed hybrid models for credit rating classification outperform the listed models in this work. A set of decision rules for classifying credit ratings is extracted.

Dash and Das (2013) comparethe performance of public sector banks with private-foreign banks under the CAMELS framework (based on the evaluation of five critical elements of a financial institution's operations: Capital adequacy, Asset quality, Management soundness, Earnings and profitability, and Liquidity). The data used for the study were the audited financial statements of a sample of 58 Indian banks which 29 were public sector banks, and 29 were private sector-foreign banks for the period 2003-2008.The financial variables and financial ratios based on the CAMELS framework, used in the analysis were: Tier I capital, Tier II capital, and capital adequacy ratio (for capital adequacy); gross non-performing assets, net non-performing assets, and net non-performing assets to total

[1]The Bankscope database is a comprehensive, global database containing 16 years of detailed financial information, including balance sheets, income statements, ratings, ratios, news, peer analysis, statistical analysis, and ownership and subsidiary information for 29,000 public and private banks in Europe, North America,Japan, Russia, and other countries. Bureau van Dijk Electronic Publishing (BvDEP), one of the world's leading publishers of electronic business and company information, created the Bankscope database for use by multinationals. The Bankscope database also contains the bank credit and country ratings of major credit rating agencies, including those of S&P, Moody's, and Fitch.

advances ratio (for asset quality); total investments to total assets ratio, total advances to total deposits ratio, business per employee, and profit after tax per employee (management soundness); return on net worth, operating profit to average working fund ratio, profit after tax to total assets ratio (for earnings and profitability); government securities to total investments ratio and government securities to total assets ratio (for liquidity); and beta (for sensitivity to market risk).The results show that private/foreign banks fared better than public sector banks on most of the CAMELS factors in the study period. The two contributing factors for the better performance of private/foreign banks are management soundness and earnings and profitability.

Hau,*et al.* (2013) examine the quality of credit ratings assigned to banks by the three largest rating agencies (Standard and Poor's, Moody's and Fitch) over the period 1990 to 2011. They define a new ordinal metric of rating error based on banks expected default frequencies, and interpret credit ratings as relative assessments of creditworthiness. The results suggest that on average large banks receive more positive bank ratings, particularly from the agency to which the bank provides substantial securitization business. These competitive distortions are economically significant and contribute to perpetuate the existence of 'too-big-to-fail' banks. They also show that, overall, differential risk weights recommended by the Basel accords for investment grade banks bear no significant relationship to empirical default probabilities.

Gogas,*et al.* (2014) present an empirical model designed to forecast bank credit ratings using only quantitative and publicly available information from their financial statements. They use the long-term ratings provided by Fitch in 2012. The sample consists of 92 US banks and publicly available information in annual frequency from their financial statements over the period (2008 -2011). In order to select the most informative regressor from a long list of financial variables and ratios, they use stepwise least squares and select several alternative sets of variables. Afterward, these sets of variables are used in an ordered probit regression setting to forecast the long-term credit ratings. The results reveal that the best model that reaches an 83.70 percent forecasting accuracy is the one that contains nine financial variables. Five of these nine forecasting regressors come from the bank's balance sheets, three are performance ratios and one comes from the income statement.

Murcia, *et al.* (2014) attempt to identify the determinant factors of credit rating in Brazil. The sample comprised a total of 153 credit rating observations issued to companies operating in Brazil during the period 1997-2011 by two major global agencies: Standard & Poor's and Moody's. The study built a Generalized Estimating Equations (GEE) model using a panel structure with credit rating as the dependent variable and ten other independent variables, namely: leverage, profitability, size, financial coverage, growth, liquidity, corporate governance, control, financial market performance, and internationalization. The empirical results show that five variables are statistically significant: leverage, profitability, growth, financial market performance and internationalization.

To the best of authors' knowledge, there are no studies in Jordan that tackle the issue of the credit ratings of the commercial banks. This study fills the gap by investigating the determinants of Moody's credit ratings of Jordanian commercial banks and suggesting a model to forecast banks' credit ratings based on publically available financial data.

## 3. Data and Methodology

The data of the study consists of the financial reports of 13 commercial banks in Jordan over the period (2000-

2013).The data will be obtained from Amman Stock Exchange. Generally, bank ratings are based on five main areas of fundamental analysis, namely capital adequacy, asset quality, management, earnings and profitability, funding and liquidity (CAMEL). According to Moody's (2002), capital is an important indicator for bank solvency and helps to support confidence among investors by offering a cushion against losses. Asset quality is central to bank solvency and therefore isimportant for maintaining confidence among investors. Management quality, the most challenging category to capture qualitative characteristics, such as attitude towards risks, experience and integrity, which directly affect the bank's efficiency and riskiness. Earnings capacity relates to the franchising value and the profitability of the bank. It is the first line of defense for debt holders in periods of stress and is considered by Moody's as the cornerstone of bank credit assessment. Liquidity is relevant to bank credit assessment because banks are susceptible to loss of confidence and sudden withdrawals of funds. Due to the maturity transformation role that banks perform and their high levels of leverage and intrinsic opaqueness, liquidity problems may become funding problems and even lead to insolvency. Based on that, our study uses a similar approach, the financial variables that are investigated in our study are, profitability, asset quality, liquidity, capital adequacy and size. Indeed, the methodology of the study is based on estimating an ordered probit regression model for the Jordanian banks to forecast a credit score for each bank over the period (2000-2013) and to determine the factors that significantly affect credit ratings. We use the ordered probit model because of its nature as an econometric model in which the dependent variable represents a ranking variable that can be used as a credit rating score. Many previous studies have utilized the same model (see for example,Afonso, *et al*., 2009; Hung *et al*., 2013;Gogas, *et al.*, 2014).

***The Model***

The probit model is a type of regression where the dependent variableis a dummy variable that can only take two values, one or zero. The name is from the words probability and unit. The purpose of the model is to estimate the probability that an observation with particular characteristics will fall into one of the two categories. On the other hand, the selection of the ordered probit model is based on the nature of the dependent variable which is discrete and ordinal that is the credit ratings. Thus, the dependent variable in the ordered probit model is a dummy variable that falls into one of three categories or more. The ordered probit model takes into account the differences between the categories of the dependent variable. For example, the difference between the rating categories 0 and 1 is not the same as 1 and 2. Thus, it is the most appropriate econometric methodology to forecast credit ratings (McKelvey and Zavoina, 1975; Trevino and Thomas, 2000). In an ordered probit model the dependent variable y represents ordered observations or in other words a ranking variable.

The dependent variable in our study is modeled by a latent variable $Y^*$that has a linear relation with a vector of explanatory variable $X_i$ , with parameter vector β, and an error term $e_i$ as follows:

$Y^*= X_i \beta+ e_i$

Where:

$Y^*$= an unobserved latent variable which represents the credit score. The observed credit score is constructed on a yearly basis, every bank is given a rank ranging from 1 to 13 according to Moody's ratings which is obtained from the Association of Banks in Jordan .

$X_i$ = a vector of explanatory variables

β= a vector of parameter

$e_i$ = random error

Typically, $Y^*$ is unobserved. What is observed are the historical Moody's credit ratings, which range from 1 to 13 over the period( 2000-2013). The forecasted $y_i$is fitted from $Y^*$ where :

$y_i = 1$ if $Y^* \leq u_1$

$y_i = 2$ if $u_1 < Y^* \leq u_2$

$y_i = 3$ if $u_2 < Y^* \leq u_3$

$y_i = 4$ if $u_3 < Y^* \leq u_4$

...

$y_i = 13$ if $Y^* > u_{12}$

This is a form of interval decision rule. The u's are threshold values (or cut points) that define the ranges of credit score (i.e., 1, 2, ... 13); which are estimated by stata.

The explanatory variables consist of four ratios that measure profitability, two measures of asset quality, four measures of liquidity, two measures of capital adequacy, and one measure of size. Also, the age of the bankis included in the explanatory variables. The following model represents them:

$Y^*= \beta_1$NIM+ $\beta_2$ROA+ $\beta_3$DPO+ $\beta_4$CTI+$B_5$LLRGL+ $\beta_6$LLPNIR+ $\beta_7$LTA+ $\beta_8$LTD+ $\beta_9$LTDB+ $\beta_{10}$LATD+ $\beta_{11}$ETA+ $\beta_{12}$ETL++ $\beta_{13}$LNASSET+ $\beta_{14}$LNAGE+ $e_i$

Where:

$Y^*$= an unobserved latent variable which represents the credit score

β= a vector of parameter

NIM= net interest revenue to average total earning assets, ROA= return on average assets, DPO = dividends per share to earnings per share, CTI= total operating expense to net revenue, LLRGL= loan loss reserves to gross loans, LLPNIR= loan loss provisions to net interest revenue, LTA= loans to total assets, LTD= loans to customer and short-term funding, LTDB= loans to total deposits and borrowings, LATD= liquid assets to customer and short-term funding, ETA= book value of equity to total assets, ETL= book value of equity to loans, LNASSET= logarithm of the total assets, LNAGE= logarithm of the years of the bank age.

$e_i$ = random error

Then, the probability of having each value of $y_i$ is estimated as follows:

Prob(1) = $\Phi$ ($u_1$-βx),

Prob(2) = $\Phi$ ($u_2$-βx) - $\Phi$ ($u_1$-βx),

…

Prob(13) = 1- $\Phi$ ($u_{12}$-βx).

Where,Φ is the cumulative function of a normal distribution.

Thereafter, the maximum log-likelihood function is used to estimate the marginal probabilities(the marginal values of $y_i$ with the beta coefficients).

$$\log l(\beta, y) = \sum_{i=1}^{N} \sum_{J=0}^{N} \log( prob\,(y_i = j / x_i, \beta, u)).1(y_i = j)$$

The last part of the equation corresponds to an indicator function which takes the value 1 if the condition is true and 0 if the condition is false.

Table (1) presents the summary of definitions of these variables and the variable codes assigned to them.

**Table 1. The definitions of the study variables**

| Variable code | Variable name and Brief Explanation |
|---|---|
| **Profitability** | |
| NIM | Net interest margin =net interest income/average total earning assets |
| ROA | Return on average assets =net income/average total assets |
| DPO | Dividend Payout |
| CTI | Cost to income ratio =overheads/(net interest revenue+ other operating income) |
| **Asset Quality** | |
| LLR/GL | Loan loss reserves(LLR)/gross loans (where gross loans=loans+ LLR) |
| LLP/NIR | Loan loss provisions(LLP)/net interest revenue |
| **Liquidity** | |
| LTA | Loans to total assets |
| LTD | Loans/customer and short-term funding (loans to deposits ratio) |
| LTDB | Loans/total deposits and borrowings |
| LATD | Liquid assets/customer and short-term funding |
| **Capital Adequacy** | |
| ETA | Equity to total assets =book value of equity/total assets |
| ETL | Equity to loans =book value of equity/loans |
| **Size** | |
| LNASSET | Logarithm of total assets |
| **Age** | |
| LNAGE | Logarithm of Years of bank age |

## 4. Results of Analysis

### 4.1 Descriptive Statistics

Table (2) presents a summary descriptive statistics of the independent variables. We calculate the minimum, maximum, mean and standard deviation for allfourteen variables over the study period.Interestingly, the size of sample banks measured by the total assets averages JD 2,940,000,000[2]. The banks in the sample vary on average from small (with a minimum total assets value of JD 53,385,252) to large banks (with a maximum total assets value of JD 24,500,000,000). The logarithm of total assets

[2]The exchange rate is : 1JD=$1.4

is used as a proxy for the size of the bank for estimation purposes thereafter. The averages of NIM and ROA are 2.8% and 1.24%, respectively. The maximum and minimum values of the profitability ratios indicate that the Jordanian banks are highly divergent in terms of their profitability. The age of the sample banks ranges from a minimum value of 17 years and a maximum of 83 years. The descriptive statistics of all liquidity, capital adequacy and asset quality ratios are also reported. Once again these ratios are different among the Jordanian banks; ETL for example ranges from a minimum value of 2% to a maximum value of 56 times. LATD ranges from a minimum value of 19% to a maximum value of 88.6%.

**Table 2. Descriptive Statistics**

| Varia | Mean | Media | Max | Min | SD |
|---|---|---|---|---|---|
| Age | 42.230 | 37.000 | 83.0000 | 17.00 | 16.416 |
| Size | 294000 | 91400 | 245000 | 5338 | 556000 |
| NIM | 0.0280 | 0.0278 | 0.0745 | 0.007 | 0.0084 |
| ROA | 0.0124 | 0.0134 | 0.0497 | - | 0.0099 |
| DPO | 0.3121 | 0.2932 | 1.2305 | 0.000 | 0.3049 |
| CTI | 0.5570 | 0.3751 | 0.8765 | 0.137 | 0.3840 |
| LLR | 0.0742 | 0.0556 | 0.9182 | 0.004 | 0.0882 |
| LLPN | 0.2116 | 0.1440 | 2.5452 | - | 0.3050 |
| LTA | 0.8876 | 0.4324 | 47.4800 | 0.002 | 4.3869 |
| LTD | 1.5061 | 0.5836 | 67.1900 | 0.004 | 7.1750 |
| LTD | 0.5754 | 0.5717 | 0.9799 | 0.003 | 0.1555 |
| LAT | 0.4420 | 0.4450 | 0.8855 | 0.189 | 0.1290 |
| ETA | 0.1194 | 0.1215 | 0.2196 | 0.006 | 0.0443 |
| ETL | 0.5952 | 0.2784 | 55.5980 | 0.018 | 4.1239 |

### 4.2 Correlation Matrix

Table (3) shows the correlation matrix between the variables of the study. The values of correlation coefficient between variables show nomulticollinearity problem.

**Table 3.**

| | CTI | DPO | ETA | ETL | LATD | LLPNIR | LLRGL | LNAGE | LNASSET | LTA | LTD | LTDB | NIM | ROA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CTI | 1.0000 | -0.2780 | -0.5104 | -0.0598 | 0.5533 | 0.5980 | 0.4691 | 0.0175 | -0.4258 | 0.0615 | -0.1051 | -0.2434 | -0.4816 | -0.6755 |
| DPO | -0.2780 | 1.0000 | 0.2351 | -0.0666 | -0.1289 | -0.1818 | -0.2007 | 0.1744 | 0.3781 | 0.0037 | 0.0237 | -0.1859 | 0.2050 | 0.1153 |
| ETA | -0.5104 | 0.2351 | 1.0000 | 0.0770 | -0.2264 | -0.2896 | -0.2867 | -0.0393 | 0.1340 | 0.0389 | 0.1082 | 0.0393 | 0.2089 | 0.3993 |
| ETL | -0.0598 | -0.0666 | 0.0770 | 1.0000 | 0.0406 | -0.0740 | 0.7066 | 0.0387 | -0.1074 | -0.0140 | -0.0118 | -0.2838 | 0.4109 | 0.0683 |
| LATD | 0.5533 | -0.1289 | -0.2264 | 0.0406 | 1.0000 | 0.0923 | 0.2488 | 0.1647 | -0.2471 | 0.0662 | -0.1264 | -0.3596 | -0.4197 | -0.2324 |
| LLPNIR | 0.5980 | -0.1818 | -0.2896 | -0.0740 | 0.0923 | 1.0000 | 0.2332 | -0.1622 | -0.1717 | -0.0447 | -0.0541 | -0.1281 | -0.3397 | -0.4809 |
| LLRGL | 0.4691 | -0.2007 | -0.2867 | 0.7066 | 0.2488 | 0.2332 | 1.0000 | 0.0741 | -0.3476 | 0.0434 | -0.0673 | -0.3432 | 0.0646 | -0.2960 |
| LNAGE | 0.0175 | 0.1744 | -0.0393 | 0.0387 | 0.1647 | -0.1622 | 0.0741 | 1.0000 | 0.4964 | 0.0128 | -0.0041 | -0.2757 | 0.0176 | -0.1615 |
| LNASSET | -0.4258 | 0.3781 | 0.1340 | -0.1074 | -0.2471 | -0.1717 | -0.3476 | 0.4964 | 1.0000 | -0.1430 | 0.0055 | -0.0398 | 0.1426 | 0.1707 |
| LTA | 0.0615 | 0.0037 | 0.0389 | -0.0140 | 0.0662 | -0.0447 | 0.0434 | 0.0128 | -0.1430 | 1.0000 | 0.2810 | 0.0451 | 0.0048 | -0.0273 |
| LTD | -0.1051 | 0.0237 | 0.1082 | -0.0118 | -0.1264 | -0.0541 | -0.0673 | -0.0041 | 0.0055 | 0.2810 | 1.0000 | 0.0011 | 0.0623 | 0.0352 |
| LTDB | -0.2434 | -0.1859 | 0.0393 | -0.2838 | -0.3596 | -0.1281 | -0.3432 | -0.2757 | -0.0398 | 0.0451 | 0.0011 | 1.0000 | 0.2596 | 0.2092 |
| NIM | -0.4816 | 0.2050 | 0.2089 | 0.4109 | -0.4197 | -0.3397 | 0.0646 | 0.0176 | 0.1426 | 0.0048 | 0.0623 | 0.2596 | 1.0000 | 0.3617 |
| ROA | -0.6755 | 0.1153 | 0.3993 | 0.0683 | -0.2324 | -0.4809 | -0.2960 | -0.1615 | 0.1707 | -0.0273 | 0.0352 | 0.2092 | 0.3617 | 1.0000 |

### 4.3 Ordered Probit Model

Table (4) reports the estimation results of the ordered probit model.The results of the profitability ratios show that there is a statistically significant positive relationship between the NIM and the bank credit rating. Thus, a higher NIM increases the probability for the bank to have a higher credit rating. Same results for ROA. On the other hand, there is a statistically significant negative relationship between the CTI and the bank credit rating. Thus, a lower CTI increases the probability for the bank to have a higher credit rating. There is no statistically significant relationship between DPO and the credit rating of the bank. With regard to the asset quality ratios, the results show a statistically significant positive relationship between the LLRGL or the LLPNIR and the bank credit rating. Consequently, the bank with a higher LLRGL or LLPNIR is more likely to have a higher credit rating. In general, the liquidity ratios show a significant positive effect on the credit rating of the bank. There is a statistically significant positive relationship between the LTA and the bank credit rating. Therefore, a higher LTA increases the probability for the bank to have a higher credit rating. The results are similar for LATD. In contrast, there is a statistically significant negative relationship between the LTD or LTDB and the bank credit rating. Hence, a lower LTD or LTDB increases the probability for the bank to have a higher credit rating. With respect to capital adequacy ratios, Table (4) shows that there is a statistically significant positive relationship between the ETA and the bank credit rating. Therefore, the bank with a higher ETA is more likely to have a higher credit rating. The results are consistent for the ETL. Finally, there is a statistically significant positive relationship between the Size and the bank credit rating. Consequently, a higher Size increases the probability for the bank to have a higher credit rating. However, there is no statistically significant relationship between the Age and the credit rating of the bank.The overall $R^2$ of the model is 53%.Thus, the examined ratios in the model explains 53% of the probability of having a higher credit rating. Our results are consistent with (Pasiouras, *et al.,* 2007) who find that equity to customer and short term funding and net interest margin are from the most important financial variables that affect the credit ratings of Fitch on Asian banks.Moreover, our results are in harmony with (Bheenick and Treepongkaruna, 2011) who find that asset quality, liquidity risk, operating performance and capital adequacy are the key determinants of British and Australian bank ratings provided by Standard & Poor's, Moody's, and Fitch.Gogas, *et al.* (2014) also report that the income statement and balance sheet ratios of US banks do significantly affect the long-term ratings provided by Fitch.

Overall, our results indicate that profitability ratios, asset quality ratios, liquidity ratios, capital adequacy ratios and the size of the bankhave statistically significant effects on the banks credit ratings. This has important implications to banks' managements and central bank. Thus, enhancing the credit rating either for a certain bank or for the whole banking system will depend mainly on these ratios as vital measures of performance.

**Table 4. The estimation results of the ordered probit model**

| Variables | Coef. | Std. Err. | z | P>z |
|---|---|---|---|---|
| Age | 0.1265 | 0.3900 | 0.3200 | 0.7460 |
| Size | 4.4310 | 0.3768 | 11.7600 | 0.0000 |
| NIM | 190.5569 | 63.3062 | 3.0100 | 0.0030 |
| ROA | 105.8644 | 47.6419 | 2.2200 | 0.0260 |
| DPO | 0.4453 | 0.3825 | 1.1600 | 0.2440 |
| CTI | -5.8605 | 0.8218 | -7.1300 | 0.0000 |
| LLRGL | 10.3765 | 3.0020 | 3.4600 | 0.0010 |
| LLPNIR | 1.3181 | 0.3760 | 3.5100 | 0.0000 |
| LTA | 0.0231 | 0.0080 | 2.9000 | 0.0040 |
| LTD | -0.0095 | 0.0035 | -2.7400 | 0.0060 |
| LTDB | -3.5230 | 1.5538 | -2.2700 | 0.0230 |
| LATD | 20.7829 | 8.7086 | 2.3900 | 0.0170 |
| ETA | 54.6818 | 11.7735 | 4.6400 | 0.0000 |
| ETL | 9.9618 | 2.7566 | 3.6100 | 0.0000 |

### 4.4 Marginal effects

Table (5) shows the marginal effects of the variables of the study on the credit rating. The estimated results show that the increase in NIM and ROA by 1% will increase the probability of the bank of havinga higher credit rating by 0.0063 and 0.0032, respectively .In contrast , the decrease in CTI by 1% will increase the probability of the bank of having higher credit rating by 0.0088. The results of the asset quality ratios show that the increase in LLRGL and LLPNIR by 1% will increase the probability of the bank of having a higher credit rating by 0.0076 and 0.0008, respectively. With respect to liquidity ratios, the rise in LTA and LATD by 1% will increase the bank probability of having a higher credit rating by 0.0009 and 0.0021, respectively. On the other hand, the decrease in LTD and LTDB by 1% will increase the probability of the bank of havinga higher credit rating by 0.0043, and0.0023, respectively. The results of the capital adequacy ratios show that the increase in ETA and ETL by 1% will increase the probability of the bank of having a higher credit rating by 0.0078 and 0.0069, respectively. Finally, when the Size of the bank increases by one JDits probability of having a higher credit rating will increase by0.0156.

**Table 5. The estimation results of the marginal effects**

| Variables | dy/dx | Std z | p>z | x |
|---|---|---|---|---|
| Age | 0.0000 | 0.3200 | 0.7460 | 3.6683 |
| Size | 0.0156 | 11.7600 | 0.0000 | 20.8267 |
| NIM | 0.0063 | 3.0100 | 0.0030 | 0.0280 |
| ROA | 0.0032 | 2.2200 | 0.0260 | 0.0124 |
| DPO | 0.0000 | 1.1600 | 0.2440 | 0.3121 |
| CTI | -0.0088 | -7.1300 | 0.0000 | 0.5570 |
| LLRGL | 0.0076 | 3.4600 | 0.0010 | 0.0740 |
| LLPNIR | 0.0008 | 3.5100 | 0.0000 | 0.2116 |
| LTA | 0.0009 | 2.9000 | 0.0040 | 0.8876 |
| LTD | -0.0043 | -2.7400 | 0.0060 | 1.5061 |
| LTDB | -0.0023 | -2.2700 | 0.0230 | 0.5754 |
| LATD | 0.0021 | 2.3900 | 0.0170 | 0.4420 |
| ETA | 0.0078 | 4.6400 | 0.0000 | 0.1156 |
| ETL | 0.0069 | 3.6100 | 0.0000 | 0.5842 |

Our results are consistent with (Adams *et al*.,2003),who find evidence that the ratings of S&P and A.M Best (credit rating agencies) are positively linked to capital adequacy ratios, liquidity ratios , profitability ratios, and size. Their study focuses on the insurance industries in UK.

Moreover, our results are consistent with (Gray *et al*., 2006), who study the credit rating of Australian firms and find that profitability ratios are greater for the firms with higher credit ratings.In addition, our findings are in harmony with (Shiu and Chiang, 2008), who find evidence suggesting that profit, liquidity, and size have a positive impact on the ratings. Their study focuses on the Lloyd’s market. Finally, our results are consistent with (Apergis*et al*., 2012) , who study the credit ratings of U.S banks. Their results show that upgraded banks are positively related to profitability, size, and liquidity.

On the whole, our results indicate that the size of the bank has the most relative importance in the credit rating of the bank followed by the capital adequacy ratios then the profitability and asset quality ratios and finally the liquidity ratios. This has important implications to banks’ managers, customers, investors and the regulatory body. Thus, banks that have these measures better would have better credit rating and would have more credit worthiness.

### 4.5 Forecasted Credit Rating

Table (6) displays a forecasted credit rating for the Jordanian commercial banks estimated according to the proposed model.

**Table 6. Theforecasted credit ratings of the Jordanian commercial banks**

| Name of The Bank | Forecasted |
|---|---|
| ARAB BANK | 1 |
| THE HOUSING BANK FOR | 2 |
| JORDAN AHLI BANK | 3 |
| JORDAN KUWAIT BANK | 4 |
| BANK OF JORDAN | 5 |
| CAIRO AMMAN BANK | 6 |
| BANK AL ETIHAD | 7 |
| CAPITAL BANK OF JORDAN- | 8 |
| JORDAN COMMERCIAL BANK | 9 |
| INVEST BANK | 10 |
| ARAB BANKING CORPORATION | 11 |
| ARAB JORDAN INVESTMENT | 12 |
| SOCIETE GENERALE DE | 13 |

Table 6 indicates that the Arab Bank, the Housing Bank for Trade and Finance and the Jordan Ahli Bank are the first three banks in Jordan in terms of their credit worthiness. On the other hand, Arab Banking Corporation -Jordan, Arab Jordan Investment Bank and Societe Generaleare the last three banks in Jordan in terms of their credit worthiness. Other banks are in between the two categories. These results have important implications to banks' customers, investors, employees and to the regulatory agency represented by the central bank. Thus, ratings convey information to the market about banks' credit quality. Depositors would prefer banks with higher credit ratings to guarantee the safety of their deposits. Investors would also concern about the credit rating of the bank as an indication to its financial position and its expected future growth and profitability. Moreover, Credit ratings give important implications to the central bank regarding the capital adequacy requirements of the banks, thus banks with low credit ratings are expected to have high levels of credit and liquidity risks. Even employees in banks with high credit ratings would have a safer career than others in banks with low credit ratings.

## 5. Conclusions

1. This study investigates the factors that affect the credit ratings of the Jordanian commercial banks over the period (2000-2013) using an ordered probit model. Moreover, the study estimates a forecasted credit rating of the banks investigated. The results show that the profitability ratios have a statistically significant effect on credit ratings. In specific, the higher the return on assets, the net interest margin, thenet interest revenue to average total assets, and the lower the cost to income ratio the more the probability for the bank to have a higher credit rating.The asset quality ratios also have a statistically significant effect on credit ratings. Particularly, the higher the loan loss reserves to gross loans, and the loan loss provisions to net interest revenue the more likely for the bank to have a higher credit rating.The liquidity ratios of the Jordanian commercial banks have a statistically significant effect on their credit ratings. Mainly, the higher the loans to total assets, the liquid assets to deposits, and the lower the loans to deposits ratio, and the loans to deposits and borrowings ratio the more the probability for the bank to have a higher credit rating.The capital adequacy ratiosalso have a statistically significant effect on bank credit ratings. In specific, the higher the equity to total assets, the equity to loans, and the equity to deposits the more likely for the bank to have a higher credit rating.The size of the bank has a statistically significant effect on its credit rating. The forecasted credit rating of the Jordanian commercial banks over the period (2000-2013) shows that the Arab Bank, the Housing Bank for Trade and Finance, and the Jordan Ahli Bank are the first three banks in

Jordan in terms of their credit worthiness.Future research could consider other factors that could affect the bank credit ratings, for example, the corporate governance factors, and the competitive position of the firm.Additionally, other researchers could use different methodologies such as neural networks,data envelopment analysis and stepwise regressions to examine the same research topic.

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# محددات التصنيفات الإئتمانية للبنوك: دليل من الأردن

***ديما وليد حنا الريضي[1]، رند سمير حمارنة[2]***

## ملخص

تبحث هذه الدراسة في العوامل التي تحدد التصنيف الإئتماني الذي تجريه شركة مودي للبنوك التجارية الأردنية باستخدام نموذج الاحتمال الترتيبي حيث تقترح هذه الدراسة نموذج للتنبؤ بالتصنيف الإئتماني للبنوك التجارية باستخدام بيانات مالية عامة معلنة في قوائمها المالية. تتكون عينة الدراسة من 13 بنكاً تجارياً أردنياً على الفترة (2000–2013). تقوم الدراسة أيضاً بتقدير تصنيف إئتماني متوقع باستخدام النموذج المقترح. تبين النتائج بأن نسب الربحية وجودة الأصول و السيولة و كفاية رأس المال و حجم البنك لها تأثير ذي دلالة إحصائية على التصنيف الإئتماني للبنوك. هذه النتائج تحمل دلالات هامة لزبائن البنوك ومستثمريها وإدارتها والسلطة التنظيمية.

**الكلمات الدالة:** التصنيف الإئتماني، البنوك التجارية الأردنية، نموذج الاحتمال الترتيبي، بورصة عمان للأوراق المالية.

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