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ASSET-BASED SUKUK RATING PREDICTION: TOWARDS BUILDING STATISTICAL AND DATA MINING MODELS

BY

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ABSTRACT

The development of sukuk market as the alternative to the existing conventional bond market has risen the issue of sukuk issuance's rating. These credit ratings fulfil a key function of information transmission in capital market. Issuers seek ratings for a number of reasons, including to improve the trust of their business counterparties or because they wish to sell securities to investors with preferences over ratings. Moreover, Basel Committee for Banking Supervision has now instituted capital charges for credit risk based on credit ratings. Basel II framework allows the bank to establish capital adequacy requirements based on ratings provided by external credit rating agencies or determine rating of its investment internally for more advance approach. For these reasons, ratings are considered important by issuers, investors, and regulators alike. Focusing on Malaysian outstanding long-term corporate sukuk from the period of 2001 to 2012, this study tries to test the efficacy and accuracy of sukuk rating model compared to the actual rating assigned by Malaysian rating agencies using statistical and data mining method, namely: Multinomial Logistic Regression, Decision Tree and Neural Network. To address the limited study on sukuk rating prediction, this research provides an empirical foundation for the investors to estimate the sukuk ratings assigned. The study examines variables from past researches on bond ratings, corporate ratings and financial distress prediction model taking into account on the various sukuk structure, credit enhancement facilities, industrial sector and macroeconomics variables. Interestingly, both statistical and data mining methods strongly indicate that share price, sukuk structure and guarantee status are empirically proven as key factors to predict sukuk rating. In addition, neural network method obtains the highest accuracy rate to predict the actual rating in the market as compared to the other two methods. Therefore, it is expected that the proposed models are beneficial to the rating agencies, sukuk issuer companies, corporate managers, private and institutional investors to support their investment decision making. The regulatory agencies may also take advantage to consider this model as benchmark for Internal Rating Based (IRB) approach as required in Basel II. In line with those practical implications, this study is also aimed to contribute the novelty aspects in the body of Islamic finance.

خلاصة البحث

إنَّ تطوير سوق الصكوك كبديل لسوق السندات التقليدية القائمة أدّى إلى ظهور مسألة تصنيف إصدارات الصكوك. هذه التصنيفات الائتمانية تؤدي وظيفة أساسية في نقل المعلومات في سوق رأس المال. ويسعى مصدّروا التصنيفات لعدد من الأسباب، بما في ذلك تحسين ثقة عملائهم في المقابلات التجارية أو لأنهم يرغبون في بيع الأوراق المالية للمستثمرين مع تفضيلات على التصنيف. وعلاوة على ذلك، فإنَّ لجنة بازل للرقابة المصرفية وضعت الآن رسوماً لمخاطر الائتمان على أساس التصنيفات الائتمانية. يسمح إطار بازل (||) للبنك بإنشاء متطلبات كفاية رأس المال على أساس التقديرات التي تقدمها وكالات التصنيف الائتماني الخارجية أو تحديد تقييم استثماراتما داخلياً لنهج متقدم أكثر. ولهذه الأسباب، تعتبر التصنيفات مهمة من قبل الشركات المصدرة والمستثمرين والمنظمين على حدٍّ سواء. تقدّم هذه الدراسة أساساً تجريبياً للمستثمرين لتقدير السندات المحددة، مع اعتماد متغيرات من الأبحاث الماضية على تصنيفات السندات، ونموذج تنبؤ تقييم الشركات والضوائق المالية، مع الأخذ بعين الاعتبار اختلاف هيكل الصكوك، مرافق تعزيز الائتمان، ومتغيرات القطاع الصناعي والاقتصاد الكلي. وبالتركيز على الصكوك الماليزية البارزة على المدى الطويل في عام ٢٠٠١-٢٠١٢، تحاول هذه الدراسة اختبار فعالية ودقة نموذج تصنيف الصكوك مقارنة مع التصنيف الفعلى من قبل وكالات التصنيف الماليزية باستخدام الطرق الإحصائية واستخراج البيانات، وهي: الانحدار متعدد الحدود اللوجستية ، شجرة القرار والشبكة العصبية. ومن المثير للاهتمام أنَّ كلًّا من الطرق الإحصائية واستخراج البيانات أشارت إلى أن سعر السهم، هيكل الصكوك وضمان حالته، هي عوامل رئيسية للتنبؤ بتصنيف الصكوك. بالإضافة إلى ذلك، فإنَّ طريقة الشبكة العصبية حصلت على أعلى معدل دقة تنبؤ التصنيف الفعلى في السوق بالمقارنة مع الطريقتين الأخرتين. ولذلك، فإنه من المتوقع أن النماذج المقترحة تعود بالفائدة على وكالات التصنيف، والشركات المصدرة للصكوك ، ومدراء الشركات والمؤسسات الاستثمارية الخاصة والصناعية لدعم اتخاذ القرارات الاستثمارية. بغض النظر عن ذلك، يجوز للوكالات التنظيمية أيضاً الاستفادة من هذا النموذج كمعيار للتصنيف المعتمد الداخلي (IRB) كما هو مطلوب في بازل (II). وتماشيا مع تلك الآثار العملية فإنَّ هذه الدراسة تهدف أيضا إلى المساهمة في الجوانب الحديثة من المعرفة المالية الإسلامية.

APPROVAL PAGE

The thesis of Tika Arundina has been approved by the following:

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DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

Tika Arundina

Signature

Date

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ΤO

My beloved husband Fauzan Priwadi My beloved parents, Aswin Naldi Sahim and Rafnis Rahman And My Supervisor, Prof Azmi Omar, who makes this happen

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In the name of Allah, the most gracious and the most merciful.

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LIST OF ABBREVIATIONS

AIArtiticial IntelligenceAT&TAmerican Telephone and Telegraph CompanyBISBank for International SettlementBPBack PropagationCAMELCapital Adequacy, Asset Quality, Management Assessment, Earnings Quality, Liquidity and FundingCAPMCapital Asset Pricing ModelCBRCase Base ReasoningCCRCorporate Credit RatingCFOCash flow from operationCRICountry Risk IndicatorDTDDistance To DefaultEBITEarnings before Interest and TaxEBITREarnings before Interest and Taxes and RentEBITDAEarnings before Interest, Tax and Depreciation AmortizationECAIExternal Credit Assessment InstitutionsEDFExpected Default FrequencyEPSEarnings before Interest, Tax and Depreciation AmortizationECAIExternal Credit Assessment InstitutionsEDFExpected Default FrequencyEPSEarnings before Interest, Tax and Depreciation AmortizationECAIExternal Credit Assessment InstitutionsIFISIslamic Finance Information ServiceFFOFunds Flow from OperationGDPGross Domestic ProductIDRIssuer Default RatingIFIIslamic Finance Information ServiceIFISIslamic Finance Information ServiceIFSBIslamic Finance Information ServiceIFSBIslamic Finance Information ServiceIFISIslamic Finance Information ServiceIFISIslamic Finance Service BoardILP <t< th=""><th>AAIOFI</th><th>Accounting and Auditing Organization for Islamic Financial</th></t<>	AAIOFI	Accounting and Auditing Organization for Islamic Financial
AIArtificial IntelligenceAT&TAmerican Telephone and Telegraph CompanyBISBank for International SettlementBPBack PropagationCAMELCapital Adequacy, Asset Quality, Management Assessment, Earnings Quality, Liquidity and FundingCAPMCapital Asset Pricing ModelCBRCase Base ReasoningCCRCorporate Credit RatingCFOCash flow from operationCRICountry Risk IndicatorDTDDistance To DefaultEBITEarnings before Interest and TaxEBITREarnings before Interest and Taxes and RentEBITDAEarnings before Interest and Taxes and RentEBFFExpected Default FrequencyEPFExpected Default FrequencyEPSEarnings per ShareFFOFunds Flow from OperationGDPGross Domestic ProductIDRIssuer Default RatingIFIIslamic Finance Information ServiceIFSBIslamic Finance Information ServiceIFSBIslamic Finance Information ServiceIFSBIslamic Finance Crevice BoardILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLug LikelihoodRRCMalaysian Agency Rating CorporationMCMMultipe Discriminant AnalysisMDAMultipe PerceptronNMCNearest Mean ClassifierNNNeural NetworkNNCNearest Mean ClassifierNNNeural NetworkNMCNearest Mean Classifier <td></td> <td>Institutions</td>		Institutions
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BP Back Propagation CAPL Capital Adequacy, Asset Quality, Management Assessment, Earnings Quality, Liquidity and Funding CAPM Capital Asset Pricing Model CBR Case Base Reasoning CCR Corporate Credit Rating CFO Cash flow from operation CRI Country Risk Indicator DTD Distance To Default EBIT Earnings before Interest and Tax EBITDA Earnings before Interest and Tax and Depreciation Amortization ECAI External Credit Assessment Institutions EDF Expected Default Frequency EPS Earnings per Share FFO Funds Flow from Operation FPM First Passage Model GE Grammatical Evolution GDP Gross Domestic Product IDR Issuer Default Rating IFI Islamic Finance Information Service IFSB Islamic Finance Service Board ILP Inductive Logic Programming LDC Linear Discriminant Classifier LL Log Likelihood Ratio Earning Vector Quantization MARC	BIS	Bank for International Settlement
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FPMFirst Passage ModelGEGrammatical EvolutionGDPGross Domestic ProductIDRIssuer Default RatingIFIIslamic Financial InstitutionsIFISIslamic Finance Information ServiceIFSBIslamic Finance Service BoardILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	FFO	Funds Flow from Operation
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GDPGross Domestic ProductIDRIssuer Default RatingIFIIslamic Financial InstitutionsIFISIslamic Finance Information ServiceIFSBIslamic Finance Service BoardILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMDAMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	GE	Grammatical Evolution
IDRIssuer Default RatingIFIIslamic Financial InstitutionsIFISIslamic Finance Information ServiceIFSBIslamic Finance Service BoardILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered Linear Probit Model	GDP	Gross Domestic Product
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IFISIslamic Finance Information ServiceIFSBIslamic Finance Service BoardILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered Linear Probit Model	IFI	Islamic Financial Institutions
IFSBIslamic Finance Service BoardILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered Linear Probit Model	IFIS	Islamic Finance Information Service
ILPInductive Logic ProgrammingLDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered Linear Probit Model	IFSB	Islamic Finance Service Board
LDCLinear Discriminant ClassifierLLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	ILP	Inductive Logic Programming
LLLog LikelihoodLRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	LDC	Linear Discriminant Classifier
LRLikelihood RatioLTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	LL	Log Likelihood
LTRLong-term issuer credit RatingLVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	LR	Likelihood Ratio
LVQLearning Vector QuantizationMARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	LTR	Long-term issuer credit Rating
MARCMalaysian Agency Rating CorporationMCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	LVQ	Learning Vector Quantization
MCDMMulti Criteria Decision MakingMDAMultiple Discriminant AnalysisM-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	MARC	Malaysian Agency Rating Corporation
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M-LogitMultinomial LogisticMLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	MDA	Multiple Discriminant Analysis
MLPMultilayer PerceptronNBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	M-Logit	Multinomial Logistic
NBNaïve BayesNMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	MLP	Multilayer Perceptron
NMCNearest Mean ClassifierNNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	NB	Naïve Bayes
NNNeural NetworkNRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	NMC	Nearest Mean Classifier
NRSRONationally Recognized Statistical Rating OrganizationsO-LogitOrdered LogisticOLPMOrdered Linear Probit Model	NN	Neural Network
O-Logit Ordered Logistic OLPM Ordered Linear Probit Model	NRSRO	Nationally Recognized Statistical Rating Organizations
OLPM Ordered Linear Probit Model	O-Logit	Ordered Logistic
	OLPM	Ordered Linear Probit Model
	O-Logit OLPM	Ordered Logistic Ordered Linear Probit Model

OLS	Ordinary Least Square
OPBDIT	Operating Before Depreciation, Interest and Tax
OPM	Ordered Probit Model
OPP	Ordinal Pairwise Partitioning
OPR	Ordered Probit Regression
OSPM	Ordered Semi-parametric Probit Model
PSIA	Profit Sharing Investment Accounts
RAM	Rating Agency Malaysia
RBF	Radial Basis Function
RF	Random Forest
ROA	Return on Asset
ROE	Return on Equity
SIC	Standard Industrial Classification
SMO	Sequential Minimal Optimization
S & P	Standard and Poor's
SPV	Special Purpose Vehicle
SC	Securities Commissions
SMO	Sequential Minimal Optimization
SPV	Special Purpose Vehicle
SVM	Support Vector Machine
TSEC	Taiwan Stock Exchange
WEKA	Waikato Environment for Knowledge Analysis

CHAPTER ONE INTRODUCTION

1.1 BACKGROUND OF STUDY

Credit rating has become an important instrument in the modern financial services industry. It has the ability of assessing the credit worthiness of a security and its issuer, most often based on the history of borrowing and repayment for the issuer, its underlying assets, its outstanding liabilities and its overall business performance. A credit rating is essential for corporate that issue debt securities as well as for investors due to several reasons. For issuers, having a good rating is beneficial as it may improve market trust on their business. On the other hand, many investors and banks rely on the ratings to make investment and financing decisions.

Credit rating also fulfills a key function of information transmission in capital market, especially to improve risk management and market liquidity. With the presence of credit rating, issue of asymmetric information among market players can be reduced. This is because rating agencies provide information related to counterparties' credit worthiness and also on the rated securities. In addition, ratings can solve investors' problem in monitoring the securities' performance. If the rating of counterparts or investment instruments is downgraded, it may serve as a signal for investors to take action since downgrading suggests a decrease in financial performance. The greater informational efficiencies are, the better informed decision investors can make about the financial markets, and more accurate price transparencies will be.

All of the benefits as mentioned above promote development of capital market, including Islamic capital market. Islamic finance and capital market is one of the

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fastest growing segments of international financial markets. Recent innovations in Islamic finance and capital market have changed the landscape of the financial industry. One of them is Islamic securities which are known as sukuk. The use of sukuk as the alternative to the existing conventional bond has become increasingly popular in the last few years. Based on International Islamic Financial Market [IIFM] (2013), the total global sukuk attained a very impressive level of issuance from the year 2001 to January 2013 with total USD 472.68 Billion. This remarkable growth can be noticed from the significant increase in terms of sukuk issuance by more than 100 times since the year 2001, from USD 1,172 million to USD 137 billion in the year 2012. These sukuk are used as a means of raising government finance through sovereign sukuk issues, and means through which companies raise funds by issuing corporate sukuk.

The development of the sukuk market has thus raised the issue of sukuk rating. Rating is essential for the corporation that issue sukuk as well as for investors because rating will give a general picture of credit worthiness of a particular sukuk. Having a good rating tends to enhance the demand of these instruments. The rating not only reflects risk and expected performance of the sukuk, but also beneficial and assist the investor specifically banks that invest in that particular security in measuring capital charge for this investment.

Sukuk and conventional bond securities have some similarities such as fixed term maturity, has a coupon and traded in the secondary market. Tariq (2004) mentioned that sukuk has a similar function with bond, which is to enable companies to raise capital, but in a Shariah-compliant fashion, whilst at the same time expanding the investor base and offering investment opportunities for new groups. However, to some extent, theoretically there should be some differences in rating methodologies for bond and sukuk because these two instruments are different in nature. Bonds are contractual debt obligation whereby the issuer is contractually obliged to pay to bondholders, on certain specified dates, interest and principal. On the other hand, according to AAIOFI Standard no.17, sukuk are certificates of equal value that represent an undivided interest in the ownership of an underlying asset, usufruct and services or assets of particular projects or special investment activity. The sukuk holder, have a claim to the underlying assets. Consequently, sukuk holders are entitled to share in the revenues generated by the sukuk assets, as well as to share in the proceeds of the realization of the assets. Sukuk certificates are unique in the sense that the investor becomes an asset holder, hence should bear the risk of its underlying assets. Sukuk certificate holders carry the burden of these unique risks.

Furthermore, sukuk also has various structures. According to AAOIFI sukuk structures comprise Ijarah, Murabaha, Salam, Istisna, Mudaraba and Musharaka, Muzara'a (sharecropping), Musaqa (irrigation) and Mugharasa (agricultural partnership). Those structures affect the coupon payment method as well as the risk characteristics. The different nature of bond and sukuk in term of their respective credit risk exposure necessitate the need for different rating assessment.

Regardless of the different nature as viewed by the External Credit Assessment Institutions (ECAI) or credit rating agency perspective, there are no significant differences between sukuk and bond rating methodology. This argument is rational as most of the sukuk available in the market are issued based on an asset-based sukuk modes', in which rating for these sukuk mostly depend on the rating of the originator which is the same method used to rate conventional bonds. This opinion is supported

¹ The detail discussion on asset based sukuk mode is presented in Chapter 3

by Arundina and Mohd Azmi (2010) who indicated the existence of similar factors for predicting sukuk and bond. However, this study did not consider various structures of sukuk, which theoretically have different features especially in term of credit risk. Hence, the present study incorporates sukuk structure into the model in order to confirm whether sukuk structure has an impact to determine sukuk rating.

Due to existence of limited study that predict sukuk rating, the bond rating prediction model is employed as a reference as well as financial distress and corporate rating model which assess credit scoring of a particular company. These approaches are considered to have similar features with sukuk rating prediction. It is also possible to extract from rating agencies some methodology guidelines which they issued. This assessment can be done by modeling and predicting sukuk ratings of companies that have sufficient information in the public domain.

There is a need for studies in the area of sukuk rating prediction due to the fact that not all the sukuk have been rated. Even, there are many cases where ratings of the sukuk are not updated. There is a case when rating of the sukuk changes drastically from AA to default². Standard and Poor's (2005) in their statistic report shows that over 10% of all rated companies that have defaulted since 1983 to 2001. They were rated Ba2 or higher at the beginning of the year in which they defaulted. This situation therefore poses a serious threat to the investors. In line with this, it is become a necessity for investors to have their own criteria in evaluating possible underlining risks in sukuk instruments.

Study on sukuk prediction, could be beneficial to investors and is very important for further development of the Islamic capital market industry. The need to develop a model to predict sukuk rating is becoming more important considering the

² Case of Royal Mint Malaysia Berhad

high cost involved and the fact that not all securities are being rated by agencies. Huang et al. (2004) argues that credit ratings are very costly to obtain due to large investment that is needed in order to perform the credit assessment. Rating agencies require a large amount of time and human resources to do deep analysis of the issuer risk status based on various aspects. As such, not all companies can afford regular updated credit ratings from rating agencies, which makes credit rating prediction quite valuable to the investment market.

1.2 STATEMENT OF PROBLEM

Similar to conventional bank, there is capital adequacy requirement that has to be fulfilled by Islamic banks. This requirement is equally described as the capital adequacy ratio. The ratio is measured by dividing Islamic bank's eligible capital with its risk weighted asset. There are some methods to measure risk weighted asset of the Islamic bank. For sukuk, risk weighted asset is measured by calculating Islamic bank exposure on the sukuk with the risk weight of the sukuk itself. The risk weight of the sukuk varies based on sukuk rating. Meanwhile, not all of the sukuk have been rated. This situation leads to the bank to assign 100 percent risk weight to the non-rated sukuk. However, this practice does not reflect the true risk that attaches to the respective sukuk.

Accordingly, there is a need to develop models to predict sukuk rating. The model can be used to estimate an initial by the bank themselves prior to the announcement of the rating agency. Moreover, Basel Committee for Banking Supervision (BCBS) has now instituted capital charges for credit risk based on credit ratings. Basel II framework allows the bank to establish capital adequacy requirements based on ratings provided by external credit rating agencies or determine rates of its

investment internally that can be used for more advance approach. With regards to this requirement, the model can lead Islamic banks to develop an Internal Rating Based (IRB) approach.

There are several studies on bond rating prediction such as; Belkaoui (1980), Ederington et al. (1984), Duta and Shekar (1988), Singleton and Surkan (1990), Kwon et al. (1997), Chaveesuk et al. (1997), Kamstra et al. (2001), Du (2003), Huang et al. (2004), Touray (2004), Kim (2005), Cao et al. (2006), Lee (2007), Hwang et al. (2009), Hajek and Olej (2011), Mizen and Tsoukas (2012), Novotna (2012), Hajek and Michalak (2013) and Doumpos et al. (2014). Since sukuk are very new to the financial world, study on sukuk analysis is very limited, especially in the area of sukuk rating. Arundina and Mohd Azmi (2010) is one of few studies which try to examine sukuk rating determinant using Belkaoui (1980) and Touray (2004) variables.

The present study thus extend the previous research on sukuk rating using several theoretical variables adapted from bond rating prediction in previous studies with the inclusion of some additional variables such as sukuk structure, guarantee status, industrial sector and macroeconomics variables. This study tries to observe whether bond rating determinant variables can predict sukuk rating, incorporating sukuk structure variable as one of sukuk specific variable.

Rating agencies such as Fitch Ratings, Moody's, Standard and Poor's, MARC, RAM, etc., have come up with their own methodology to rate sukuk which is not publicly disclosed. Therefore, it is considered important to have research effort to provide an insight into the rating process and thus verify its credibility. Sukuk rating prediction study becomes more important in order to provide guidance for the Islamic bank in understanding sukuk risk. Hence, it is considered that research efforts directed to analyze and investigate ratings given by rating agencies would be of great benefit to