THE APPLICATION OF KMV MODEL IN THE LISTED RESIDENTIAL REAL ESTATE DEVELOPERS IN THAILAND

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Abstract- This paper applies KMV model which is a structural model to assess the credit risk to the residential real estate developers in Thailand. It shows the result of ranking of distance of default in the sample, where it varies across time. During the recent financial crisis this model also reflects into lower median of distance to default. The study also explores the sensitivity to the variations of equity volatility and default point, which are the key inputs of the model. Both variables have inverse relations with the distance to default with asymmetric impacts. Given the level of volatility and distance to default in 2014, the smaller volatility increases the distance to default more than the larger one, while the smaller distance to default increases the distance to default less than the larger one. We therefore extend that the variation of volatility tends to exert more impact on the distance to default more than the variation of default point.

Keywords- Credit Risks, Residential Developers, KMV Model, Financial Institutions, Distance to Default.

I. INTRODUCTION

Real estate development industry, particularly the residential sector worth 4.4% of overall Thailand Gross Domestic Product (GDP) in 2014 [1], however, real estate industry is the real productive sector that drives the dynamic of other industries, and stabilize the whole national economic system [2].

A residential project, by its nature, certainly requires a huge sum of development funds, and the developer seeking for that fund by making a loan with any financial institution or bank. The developer, therefore, bears a difficulty in finding the proper source of funds [3], whereas bank also holds the risk of lending a huge amount to the developer, and this criticality is regarded as “Credit risk” [4]

Credit risk in financial institutions is defined as the potential that a bank’s borrower or counterparty will fail to meet its obligations in repaying the loan borrowing from bank or any financial institutions. In this regard, banks need to manage the credit risk related to the entire portfolio whether in the form of individual or transactional credits, banks also need to consider on the relationships between credit risk and other risks, since these are a measuring criteria to assess the success of any banking organization [5].

This paper empirically examines the structural approach as an alternative method to assess the credit risk for financial institutions in Thailand towards lending to Thai real estate developers. The expected outcome of this paper is an empirical result from the model to evaluate the credit risk in the bank’s lending process. Some inferential statistics are shown in this paper along with the sensitivity of the credit risk measure based on the variation in the key inputs of the model by using the case studies of Thailand’s residential developers, who registered in Stock Exchange of Thailand (SET).

II. CREDIT RISK ANALYSIS

2.1. Current Credit Risk Analysis Procedure

Thai Commercial banks typically employ the qualitative methods to evaluate the credits and risks of the borrowers, normally based on the 5C’s principles, comprising Characters of a borrower, Capacity in repaying loan, Collateral, Capital, and Conditions of loaning contract, respectively. The assessors also employ the traditional ratios including profitability ratio, such as Return on Equity (ROE), Return on Asset (ROA), or debt and coverage ratios such as Short-term Solvency Ratios or Capitalisation Rate etc.[5].Although these methods are simple, but they normally depend on the credit assessors’ experiences, and the past performance of the borrowers, therefore those cause more subjectivity and bias to users. As the traditional methods are inept to deal with the complexity of credit risks and the bias the assessors may have, this paper applies an option theoretic structural approach, which is based on Merton’s theorem [6] in assessing the credit risk.

2.2. Structural Model

Structural models are based on quantitative method to model the economic process of firm’s default. They are derived from the incentives that the firm will default on their debts based fundamentally on the firm capital structure. It can be categorised into 2 alternatives [7] as: options-theoretic structural models and reduced form or intensity-based models. However, the authors only emphasise the options-theoretic structural models as our tools to design in studying the listed residential developers in Thailand.

Based on the option-theoretic structural models, a firm has the main incentive to default, whenever its asset value falls below some face value of a debt contract, provided that there is no possibility of refinance at that point. This point is also named as default point.

By this concept, Merton [7] applied the famous option pricing model – Black and Scholes [8] to affirm the value – henceforth called BSM model. The equity in a levered firm can be perceived as a call option on the firm’s assets with a strike price equal to the debt repayment amount. If at expiration (depending on the time horizon of the probability of default), the market value of firm’s assets exceeds the value of its debt, the shareholders will exercise the option by repaying the debt and claiming the residual values of the assets. On the other hand, if the value of the assets falls below the debt value at the expiration, the shareholders just simply allow the option to be unexercised and the firm’s shareholders will default. Thus, the probability of default until the expiration is equal to the likelihood that the option will expire without being exercised. It views the default as the gradual process.

Figure 1: Asset value evolution process and distance to default

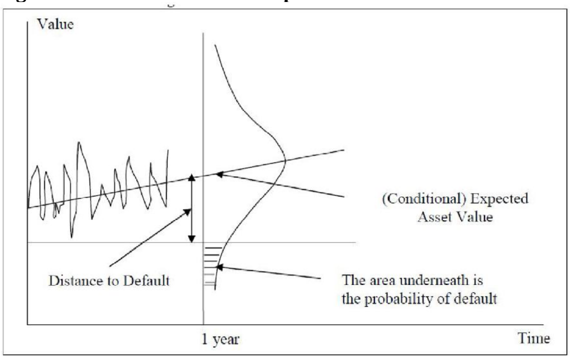


Figure 1

The distance between the default point and the asset value from the BSM model normalized by standard deviation and also known as the distance to default (DD), representing the number of standard deviations the asset value is away from default, which can be transformed in to the risk neutral probability of default using the cumulative standard normal distribution.

The key strengths of this model include 1) being based on theoretical ground by explaining the economic process of default; 2) less subjective than the traditional methods; 3) integrating more frequently updated market data to the financial statement information; and 4) forward looking by expecting the value of the company and the judgment of the company's future development trend of the investors.

Given these strengths, many researchers have extended the model by relaxing different assumption from allowing a firm to pay dividend, the debt can be a coupon paying type, etc. More recent models had been implemented include [9], [10], [11] [12].

A drawback of BSM model assumes only one class of debt and using the cumulative normal distribution to convert the distances to default to default probabilities. In 1989, the company founded by Kealhofer, McQuown and Vasicek (KMV), later acquired by Moody, uses the proprietary model which is a generalized version of the BSM model encompassing different classes of debt and also maps the attained distance to default to the expected default frequency (EDF) inferred from their database of both default and non-default firms [13]. This method has been used by Moody's as the credit rating tool worldwide.

Since the EDF used by Moody's KMV come from the companies in foreign jurisdiction, where the default process are different from Thailand. The validity of using these data is in doubt. Thus, this paper will discuss the probability of default in terms of risk neutrality or assuming the normal distribution.

III. METHODOLOGY

This paper employs the Moody's KMV model in accordance with Crosbie and Bohn [13]. The researchers selected 40 real estate developers, who are listed in SET, and their core competencies are regarded to residential projects development. In order to calculate and compare the Distance to Default (DD) and Probability to Default (PD), these values are necessary to measure the degree of companies' credit risk, the higher DD means the lower credit risk. Before the calculation of the model, there are essentially three steps of calculating the probability of default; which are;

1. Estimate asset value and volatility: Assuming that a firm's asset value follows a stochastic process with a drift and unobservable, it can be estimated along with the volatility from the market value and volatility of equity and the book value of liabilities (see Appendix I). However, these two variables cannot be calculated directly from the model. The numerical method is, therefore, implemented to solve the problem through MATLAB program.
2. Calculate the distance-to-default: It can be calculated from the estimated firm's asset value and volatility and the expression of default point as follows:

$$\text{Distance to Default} = \frac{\text{Market value of Asset} - \text{Default Point}}{(\text{Market Value of Asset} \times \text{Asset Return Volatility})} \quad (1)$$

where

$$\text{Default Point} = \text{Short-term debt} + (1/2) \times \text{Long-term debt} \quad (2)$$

3. Calculate the default probability: The default probability is determined directly from the distance-to-default, which the risk neutral probability in this study was based on cumulative normal distribution due to the lack of empirical default database for Thailand real estate industry.

IV. DATA

The study focuses on 40 companies listed in the Stock Exchange of Thailand to avoid the limitation of the market data and the transparency of the financial statement of non-listed companies. The study started by examining the 2014 dataset, which is the most updated full year dataset and compare the level of credit risk as measured by KMV model across the residential real estate developers. Also, the dataset is also expanded to cover from 2006 to 2013, in order to compare the periods before and after the global financial crisis triggered by the Sub-prime crisis in the US.

The data were divided into 2 groups including the market based and the financial statement based data. For the market based data, the authors collected the stock price to calculate the market capitalization from Bisnews/Reuters in the daily frequency. The year-end stock prices are used to calculate the market capitalization of each company while the historical volatility is calculated by annualizing the daily changes with $\sqrt{T}$, where T is the number of working day in each year. For the risk-free rate, we use 1-year government bond yield obtained from Thai BMA as a proxy since it is a market interest rate with theoretically no inherent credit risk.

The data on financial statement for each company can be obtained from Reuters Knowledge. These are the total asset, short-term debt, long-term debt, and the number of share outstanding, respectively. We choose the most updated balance sheet data for each year. The data are collected on a yearly basis because the time series characters of the distance to default are not the major objective of this paper. Moreover, the data obtained from 3rd party audited balance sheet are chosen due to their transparency and reliability.

V. RESULTS AND DISCUSSION

5.1. An interpretation of results

Based on the estimation of the distance to default and the probability of default, Table 1 shows only the top 20 distance to default of the listed residential real developers in Thailand (where the rest will be given upon request).

Table 1: Top 20 Highest Distance to Default As of December 2014

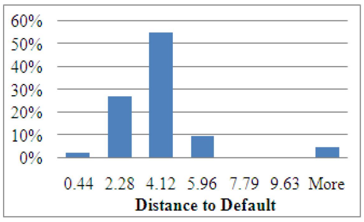
	V_E	DPT	V_A	σ_A	DD	PD
A	5,341	6,767	14,159	5%	11.47	0.000%
NOBLE	4,839	10,859	20,019	5%	10.12	0.000%
LALIN	3,515	2,154	6,175	11%	5.76	0.000%
MK	3,665	1,248	5,311	14%	5.62	0.000%
PRIN	1,964	4,848	8,294	8%	5.48	0.000%
QH	36,000	19,424	64,123	17%	4.15	0.002%
SENA	2,372	3,800	6,170	9%	4.12	0.002%
SIRI	25,348	37,796	72,365	12%	3.92	0.004%
SC	13,374	13,499	29,222	14%	3.89	0.005%
GLAND	16,975	6,595	25,572	19%	3.89	0.005%
SPALI	45,918	14,854	65,475	21%	3.70	0.011%
LH	104,363	28,798	144,897	22%	3.68	0.012%
AP	20,291	14,089	39,114	17%	3.68	0.012%
PACE	6,853	12,207	23,246	13%	3.64	0.014%
PS	66,720	22,477	97,049	22%	3.46	0.027%
MJD	2,702	7,820	10,990	9%	3.31	0.046%
PF	7,450	17,892	28,949	12%	3.22	0.064%
BLAND	37,365	4,958	42,220	28%	3.19	0.070%
ANAN	11,532	6,812	21,450	22%	3.17	0.075%
RML	7,365	6,812	14,791	18%	3.02	0.125%

Remark: V_E = market capitalization, DPT = default point, V_A = expected value of assets (one-year from now), σ_A = asset volatility, DD = distance to default, PD = probability of default

For instance, the range of distance to default is 0.44-11.47. It can be interpreted that the distance to default is 11.47, (the data from the end of 2014 to the end of 2015), thus the company has 11.47 times of standard deviations away from the default point or the (risk neutral) probability of default would be almost 0%. Nonetheless, there is no default database for Thailand to map the distance to default to probability of default and the proprietary database of Moody's KMV is prohibitively expensive for us to obtain, this paper shall only analyze and discuss on the estimated distance to default as the proxy for credit risk measure.

From the estimation of results, some statistics can be worth looking into how the distances to default distribute. It is apparent from Figure 2 that they are not normally distributed as visually seen in histogram and the null hypothesis of normality based on the Jarque-Bera Test can be also rejected. The sample also shows positively skewed distribution with the fat-tailed (Kurtosis > 3). Therefore, any statistical inferences, e.g. the measure of central tendency shall be based on non-normal and asymmetric distributions.

Figure 2: Histogram and Descriptive Statistics



Mean	3.251
Median	2.936
Max	11.470
Min	0.443
Std. Dev.	2.175
Skewness	2.070
Kurtosis	8.358
J-B Test*	76.422

Remark: * Jarque-Bera Test is significant at 99% confidence level

In addition, the mean and median from 2006 – 2014 has been plotted to show the development of the distance to default throughout time, this paper excluded the newly listed companies, who registered in SET after the aforementioned interval, especially, the period include the financial crisis starting in 2007 as stated in Federal Reserve Bank of St. Louis's report [14]. According to Figure 3, the median fell lower in 2008-2009, that is also consist with the result in Chinese market [15]. This could be a result of both higher volatility of assets and the lower asset value leading to shorter the distance between the asset value and the default point after the crisis started. Moreover, during 2013 when there was an uncertainty when the Federal Reserve planned to stop buying the long-term assets (QE program), the global stock market recessed while the volatility rose, resulting in the lower distance to default.

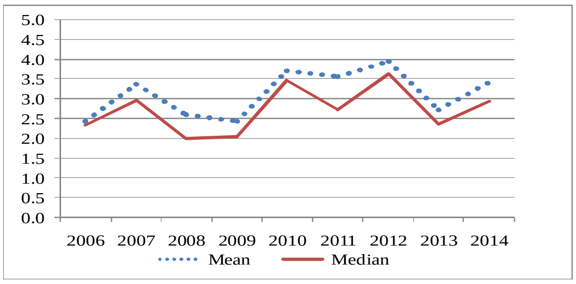


Figure 3: Mean and median of the distance of default across time

5.2. Sensitivity of the Distance to Default

The empirical result also shows that the distance to default inversely varies to the volatilities in both equity and assets. Theoretically, it can be explained through the expression of the distance to default calculation according to the equation (1) where asset values and volatilities are the inputs. Intuitively, it is interpreted that as the firm's asset value is composed of equity and liability where only market value of equity can vary in this framework. Thus, the larger volatility of the equity leads to the larger volatility in firm's asset value.

As the default point is another key input in the model, the authors investigate the impact of changes in proportion of long-term debt adding on the short-term debt, apart from the original proportion of 0.5, used by Moody's KMV [13].

To further examine the sensitivity of the distance to default to these inputs, the authors calculate the numerical results based on the sample in 2014 by varying volatility. Table 2 shows the variation of the results represented by the differences of varied outputs from the current level of default point and the volatility in 2014 (where deviation from volatility = 0 and default point = 0.5xLT (long-term debt)). At each deviation of volatility from 2014, the change in distance to default caused by the deviations from the current default point are shown in each row, while the deviations from the current volatility are exhibited in each column for each level of default point.

Table 2: Sensitivity of Distance to Default

Volatility	0.1xLT	0.3xLT	0.5xLT	0.7xLT	0.9xLT
-50%	99%	93%	85%	71%	59%
-40%	79%	71%	60%	48%	39%
-30%	57%	51%	39%	32%	20%
-20%	37%	32%	21%	15%	5%
-10%	22%	17%	8%	2%	-7%
0	13%	7%	0%	-5%	-15%
+10%	2%	-3%	-9%	-14%	-23%
+20%	-7%	-11%	-17%	-21%	-29%
+30%	-14%	-18%	-23%	-28%	-35%
+40%	-21%	-24%	-29%	-33%	-39%
+50%	-27%	-30%	-34%	-38%	-44%

From Table 2, the smaller volatility relative to that of 2014 increases the distance to default more than the larger volatility decreases it, given the same default point. For example, the distance to default increase by 85% when the volatility decreases by 50% at 0.5xLT default point, whereas the distance to default decreases by merely 34% when the volatility increases by the same magnitude of 50%.

The authors vary the default point from the original one by increasing to 0.9xLT, the distance to default would fall by 15%, while decreasing the default point to 0.1xLT, the distance to default would rise by only 13%, given the volatility in 2014.

As can be noticed from Table 2, the variation of volatility in terms of percentage would result in larger changes in the calculated distance to default than the variation of default point does.

5.3. Discussion and Further Research

The results from this study based on the distance to default as a ranking tool for credit risk assessment and can further be to construct an internal rating system for financial institutions. However, to come up with the end result of probability of default, large number of data both default and non-default companies are essential in creating a default database.

Apart from such a limitation, it must be cautioned in using this model when calculating the inputs particularly, the volatility. As seen in the analysis, the volatility has a large impact on the outcome of distance to default, especially illiquid stocks of which the prices include the liquidity premium in it. This feature can be observed through the wide gap between the bid and ask prices and no trading volume.

As the model assumes only one class of liabilities (the debt), the further research can be conducted on more classes of liabilities and it can incorporate the process of restructure which normally extends the period of time before the company actually defaults.

The study on the distance to default from the structural approach can be extended to study the impact of specific company's characteristics on the distance to default. In addition, macroeconomic variables as the proxy for the state of economy directly affecting the business financial operations of a firm, which in turn, the credit risk can also be further explored.

CONCLUSION

In this paper, the application of KMV model to the residential real estate companies listed in the Stock Exchange of Thailand is explored. The model yields the numerical credit risk measure called distance to default (DD), which are used to rank cardinally compared to other traditional credit assessment approaches.

Nonetheless, due to lack of the empirical database similar to the Moody KMV to map the distance to default to the empirical default frequency (EDF), the paper bases the analysis mainly on the distance to default rather than in an attempt to map it to the probability of default.

The paper also extends to cover the medians of distance to default across the years since 2006 and finds the lower medians in 2008 and 2013.

Then, the sensitivity of the distance to default from varying the stock volatility and the default point is addressed. The lower volatility causes the distance to default to increase larger than higher volatility, while the higher default point leads to higher change in distance to default than the lower default point does. Nonetheless, the variation of volatility tends to exert larger effects on the distance to default calculation than the variation of default point.

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Appendix I

BSM Model description

The original concept by Merton [ ] allows only one debt instrument paying a zero coupon with a face value of D and asset value of V, then the equity value of a firm can be described as follows:

$$E = \max(V_A - D, 0) \tag{A.1}$$

Where E = market capitalization (stock price x number of shares outstanding); V_A = asset value; D = book value of debt

Assuming the market value of the firm’s underlying assets follows a stochastic process A.2

$$dV_A = \mu dt + \sigma_A dZ \tag{A.2}$$

where μ, σ_A are the firm’s asset value drift rate and volatility, and dZ is a Wiener process

By substituting the risk-free rate for a drift of the asset value (μ) in Equation (A.2) and plugging in a call option formula with a continuous time in Equation (A.1), the final result corresponds to the following

$$E = V_A N(d_1) - De^{-rT} N(d_2) \tag{A.3}$$

Where V_A , E, and D are defined as above,
r is a risk-free rate
T is a time horizon (assumed to be 1 for 1-year)
N(.) is a standard normal cumulative probability distribution

$$d_1 = \frac{\ln(\frac{V_A}{D}) + (r + \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}} \tag{A.4}$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \tag{A.5}$$

By virtue of Itô Lemma, the volatility of the equity can be described as follows.

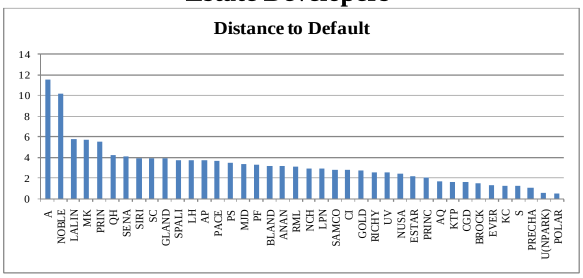
$$\sigma_E = \sigma_A \frac{V_A}{E} N(d_1) \tag{A.6}$$

Where σ_E is the volatility of equity

From Equation (A.3) to Equation (A.6), we can numerical solve for V_A and σ_A. Finally, these two parameters can be used to calculate the d2 which represents the distance to default based in the BSM model.

Appendix II

Ordering Distance to Default in Residential Real Estate Developers



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