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Predicting Corporate Defaults: Evaluating Moody's Credit Rating Institute

by

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Abstract

The ability of the Merton model and the logistic regression to accurately forecast corporate defaults is evaluated. Additionally, the probability-of-default (PD) estimates obtained from these two models are compared with the corresponding rating class historic default rates presented by Moody's. Data for 56 defaulted and 272 healthy US publicly traded organizations serves as the basis for this study. Results reveal that: (i) the logistic regression is more accurate in distinguishing between defaulted and healthy companies, but provides overly conservative PD estimates; (ii) the Merton model struggles to correctly identify true defaults and true non-defaults, while providing default probabilities that are in line with historic default rates (iii) no framework was deemed superior in this context, ascertaining the difficulty associated with identifying the precise timing of a corporate default.

KEY WORDS: Moody's, Merton Model, Logistic Regression, Probability of Default, Credit Ratings.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Credit Rating Agencies (CRAs) are among the most important members of the financial system, having the ability to influence the behavior of almost all capital market participants. Regulators use them to monitor the solvency of banks and other financial institutions, investors rely on them to observe the riskiness of their investments and to alter their portfolios accordingly, banks and other investment vehicles utilize rating migration metrics to determine the default correlation within their portfolios of assets (Du and Suo, 2007). This grants rating agencies the status of universally feared gatekeepers, particularly when the process of issuing public debt securities is taken into consideration. Since market participants do not possess nether the resources nor the time to adequately assess the risk related to investing in a specific debt instrument, they most often resort to the expertise of rating agencies, when evaluating domestic and cross-border financial transactions. CRAs therefore have a profound impact on the borrowing costs of organizations and can noticeably affect the decision process regarding their capital structure. (Schwarcz, 2002).

With that in mind, the methodology applied by CRAs is rather secretive and only one of the most renowned rating agencies, Moody's, is more explicit about its KMW model. It emphasizes the usage of three main elements in the process of determining the default probability of a company, namely the value of its assets, the riskiness of these assets, and the amount of leverage the firm has on its books. These elements are then utilized in the process of estimating the volatility of mentioned assets. All the aforementioned elements are subsequently combined together, in an effort to as accurately as possible approximate the firm specific distance-to-default (DD), which is then translated into probability-of-default (PD). The actual mechanism governing this conversion process is based on the historically observed relationship between DD and PD. The rating agency also specifies that the probability for an average publicly traded firm to default during a one year time frame is 2%. This number naturally varies quite significantly with rating classes, where an Aaa-rated organization is anticipated to have default odds of about 2 in 10,000 per annum and an A1-rated company is expected to experience bankruptcy with odds of 10 in 10,000. However, Moody's claims that prior to default, there is no unequivocal method to ascertain whether such an event will occur or not (Crosbie and Bohn, 2003). In line with this, there are two major instances that have put a significant dent in the reputation of CRAs, resulting in palpable doubts regarding their ability to assess the creditworthiness of companies and various financial instruments alike. The failure of Enron, a US based financial behemoth, in 2002 raised serious concerns about the quality of credit assessment provided by CRAs. The company had an investment grade rating, meaning that it represented a low level of default risk, awarded to it from all three major CRAs, namely Moody's, S&P and Fitch. Even though CRAs reacted to the deterioration of the company's financial strength, their reassessment of the ability of Enron to repay its creditors was arguably much slower than desirable, causing significant losses to a large pool of investors (Lieberman et. al, 2002). The Global Financial Crisis (GFC) of 2008-2009 unfortunately ascertained that this was not an isolated incident. By December 2008, the market for structured financial products in the US has ballooned. By December 2008, the market for structured financial products in the US had ballooned to $11 trillion or 35% of the total outstanding bond market in the world 's largest economy. More than half of these securities, which academics and regulators will eventually name as one of the most, if not the most important underlying causes for the GFC, were granted an Aaa rating by Moody's. Even though the rating agency eventually downgraded 36,346 of these instruments, many still blame the CRAs for their lack of timely reassessment during a period, which nearly resulted in the demise of the modern financial system (Benmelech and Dlugosz, 2010).

The reasons behind such failures of CRAs are complex and to a certain extend related to the building blocks of the entire financial system. Although it is quite clear that CRAs are not the sole culprits for the aforementioned financial disasters, there are at least three aspects related to their structure and the nature of their work, requiring the upmost attention from all market agents, which are heavily reliant on their rating assessments. Firstly, Moody's, Fitch and S&P accounted for 96.5% of all the credit ratings issued in 2013 in the US, according to data from the official report of the US Securities and Exchange Commission. This represents a relatively insignificant change from the 98.7% market share that these institutions had in 2007. This is even more troubling, when one accounts for the implication that CRAs are publicly traded entities, which are naturally concerned with profit maximization. Since their profitability is strongly related to the ability to charge fees from debt issuers, a sinister from of moral hazard arises. Due to the costly nature of risk assessments and the fact that issuers are free to choose which rating agency to commission, the latter have an incentive to assign higher ratings to the former in their strive to win market share and boost operating performance. (Mählmann, 2008). This needs to be coupled with the fact that rating agencies do not provide an absolute measure of credit risk, but rather a relative ranking for default risk from high to low. The lack of actual PD estimates is further amplified by the information that intervals and ratios between different ranks are meaningless, implying that no realistic answer can be found to questions such as whether or not a one notch downgrade from Baa3 to B1 result in the same type of risk increase as a similar downgrade from Aa3 to A1 (Mählmann, 2008).

Considering the aforementioned characteristics of CRAs and the secretive nature of the risk assessment methodology applied by them, the realization that academics have been attempting to find alternative ways to measure the riskiness of debt obligations can hardly be deemed surprising (Mählmann, 2008). One obvious answer can be found in the work of Robert Merton and his famous model from 1974. It is a structural model, resting to a high degree on the notion that the risk level associated with a particular debt obligation can be determined via the careful and thorough analysis of the issuer's balance sheet. The fixed liabilities of the company are seen as a boundary, which the total assets of the organization must not cross. If such an instance does however occur, the firm is naturally unable to service the contractual obligations and thus effectively enters default. The Merton model therefore is based on the very straightforward and rudimentary accounting principle that the equity of a company is equal to the value of its assets less its liabilities. The equity is then simply seen as a call option on the firm's assets, which at maturity pays either zero, if the value of the liabilities is larger than the value of the assets, or the difference between the asset and liability values (Gordy and Heitfield, 2002). By combining the Black and Scholes (1973) option pricing formula, with one of the most important accounting principles, the Merton model provides a viable alternative for determining the riskiness of corporate debt.

An additional large body of academic research is related to the usage of financial ratios in order to predict the failure of corporations. Unlike the Merton model, this approach is statistical in its nature and has the advantage of utilizing financial indicators, such as Cash Flow to Total Debt and Earnings Before Interest and Taxes (EBIT) to Book Value of Total Debt, which are easily available in the accounting documentation of organizations. Via the application of these and numerous other financial rations, researchers have attempted to measure the ability of organizations to fulfill their debt obligations. The utilizations of the Logit regression framework, which uses such ratios as dependent variables, has further improved the methodology, therefore solidifying its position as an additional alternative to the above listed risk assessment methodologies (Frade, 2008).

Considering that there are a number of viable ways, which can be implemented during the process of assessing the ability of an issuer to service its debt obligations, and the arguably lackluster performance of CRAs during the GFC, a comparison between the former and latter methods can be of interest. The aim of this paper is therefore twofold. First, to evaluate the ability of the Merton model and a Logit regression performed on financial ratios to accurately predict corporate defaults. Second, the resulting default probabilities obtained from the aforementioned methodologies will be compared with the historically observed default rates associated with the various rating classes of Moody's. Moody's was selected for this research because it is the rating agency that is least secretive about its methodology. Additionally, since it does not provide the public with an explicit PD for each company, historic default rates, matched with the credit rating assigned by Moody's to a business, can be deemed a reasonable metric for credit risk (Bharat and Shumway, 2004).

In order to achieve the above specified goals, data for 272 healthy and 56 defaulted, publicly traded US companies in the period between 2006 and 2012 was obtained. This time frame captures one of the most severe recessions in recent history, and is thus related to a large number of corporate defaults and high level of credit risk, making accurate PD calculations critical. Additionally, as the US market is the world's largest and is characterized with possibly the most sophisticate investor base, it can be deemed as a suitable choice in this context. Since the S&P 500 is the broadest and one of the best recognized US composites, only companies that have been listed on it for the entire period of interest will be considered for this research.

In light of the aforementioned objective of this paper and with respect to the particular data set being utilized, this study will argue that the Merton model is much closer in its assessment for default probabilities to the historically observed bankruptcy rates presented by Moody's. The logistic regression is considerably more conservative in its predictions and in some instances produces PD estimates that are unrealistically high. With that in mind, both the Merton model and the credit ratings of Moody's in some cases lack the ability to quickly adjust their PD forecasts for organizations that are nearing default. This implication leads to the conclusion that none of the approaches being considered in this work offers a satisfactory balance between conservativeness and capacity to correctly identify healthy companies that are not expected to go bankrupt.

The rest of this paper will be structured in the following fashion: the next section gives the theoretical framework, which serves as the foundation for the subsequent empirical study. It includes additional clarification regarding the methodology utilized by Moody's; a detailed explanation of all the relevant features of the Merton model; description of the logic behind Logitic regression and the financial ratios that were deemed suitable in this context; and clarification of the methodology used in the process of assessing the ability of the Merton model and the Logit regression to correctly identify healthy and defaulted companies. Section three describes details regarding the data set being used. Section four portrays the results of the empirical work and offers the relevant analysis. Finally, the last section contains the concluding remarks.

Chapter 2

Theoretical Framework

2.1 Moody's credit ratings and rating methodology

The most important role of CRAs is to present participants on the financial markets with reliable assessments of the creditworthiness of debt issuers (Hull, 2012). In this research only credit ratings from Moody's will be employed. This mirrors the approach taken in previous empirical work (see Bharat and Shumway, 2004, Tudela and Young, 2003) and is due to the less secretive nature of Moody's methodology.

The rating classes as specified by Moody's from highest to lowest are: Aaa, Aa, A, Baa, Ba, B, Caa, Ca and C (for additional information of Moody's credit ratings and historical default probabilities see Table A.2 in Appendix). As previously mentioned, the higher the credit rating, the lower is the historically observed default rate for companies that belong to this rating class. Furthermore, there are subcategories for each rating class, namely Aa1, Aa2, Aa3 for the Aa category; A1, A2, A3 for the A category etc. Only the highest rating category (Aaa) and the two lowest (Ca, C) are not divided into subcategories. Finally, an important distinction needs to be made between ratings higher than Baa, which are labeled as investment grade, and those with a lower rating, which are considered high yield or speculative grade (Hull, 2012).

2.2 Merton Model

One of the most popular approaches in the process of assessing credit risk involves the implementation of the Merton Model. A structural framework, which exploits the Black and Scholes (1973) option pricing formula, the method postulates that the firm can issue two types of securities: equity and debt. The debt is assumed to have a zero-coupon structure, implying that it pays no interest, with a maturity at a future time T. The firm enters default if the value of its assets is insufficient to repay its debt obligations at T. The company's equity is thus effectively a European call option on its assets, with a maturity T and strike price, which is equal to the value of the debt. The model requires several inputs for its implementation, namely the value of the company's assets, their volatility, the outstanding debt, and finally the equity value and volatility. Due to the fact that the market's estimation of the first two components cannot be observed, Jones et. al (1984) theorized that can be inferred from the market value of the company's equity and the volatility of the equity (Hull, Nelken and White, 2004). It is important to point out that in the context of this assumption the firm pays no dividends to its equity investors.

An additional difficulty related to the practical application of the model is associated with the maturity structure of the firm's debt obligations. As specified above, all liabilities of the organization are required to have the same maturity T, which in practice is not feasible. The work of Kealhofer (2003) and his KWM model, which has served as a foundation for the Moody's risk assessment methodology, presents a solution to this issue. This specification states that the value of the firm's debt can be calculated by simply adding the company's short-term liabilities and half of its long-term debt. Due to its simplicity and practicality, this is an assumption that will also be employed in this work (Kealhofer, 2003).

With the theoretical foundations behind the Merton Model in mind, the focus can now be turned on the actual specifications of the methodology. As already stated, the payment to shareholders in the context of the model is given by:

$$E_T = max[A_T - D, 0] \tag{2.1}$$

where E_T represents the value of the equity at time T, A_T stands for the assets of the firm when the debt matures, and D encapsulates its liabilities. In order to estimate the PD, the model assumes that the assets follow a General Brownian Motion and are normally distributed. These assumptions yield that:

$$dA = \mu_A A dt + \sigma_A A dW \tag{2.2}$$

where μ_A is the expected continuously compounded return on the A; σ_A is the volatility of A; and dW is a Wiener process. Both μ_A and σ_A are assumed to be constant in the context of this classical specification. From (2.1) it is known that the value of E_T is a function of the company's assets and debt at T. By applying the work of Black and Scholes (1973) the current equity price can be determined in the following fashion:

$$E_t = A_t N(d_1) - De^{rT} N(d_2) \tag{2.3}$$

where A_t is the value of the assets at $t = 0$, and r represents the risk free interest rate. $N(\cdot)$ is the cumulative standard normal distribution function and d_1 and d_2 are calculated by (2.4) and (2.5) below,

$$d_1 = ln\left(\frac{A_t}{D}\right) + \left(r + \frac{\sigma_A^2}{D}\right)(T - t) \tag{2.4}$$

$$d_2 = d_1 - \sigma_A \sqrt{T - t} \tag{2.5}$$

From (2.3), (2.4) and (2.5) it can be concluded that:

$$E_t = A_t N\left(\frac{ln\left(\frac{A_t}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)(T - t)}{\sigma_A \sqrt{(T - t)}}\right) - De^{rT} N(d_1 - \sigma_A \sqrt{T - t}) \tag{2.6}$$

As already specified, there are two unobservable values in this equation, namely the value of the company's assets A_t and their volatility σ_A. Thus, in order for (2.6) to be solved, one additional equation is required. When Ito's lemma is applied to $E[(A_t), t]$, given that A_t follows a Geometric Brownian Motion with a drift μ_A and volatility σ_A.

$$\sigma_E = \frac{A_t}{E_t} N(d_1)\sigma_A \tag{2.7}$$

where σ_E is the instantaneous volatility of the company's equity at time zero. The equation above allows the unobservable A_t and σ_A to be obtained from E_t and σ_E. This is done via the creation of an equation system, which includes Equations (2.6) and (2.7). Matlab is then utilized, in order to solve the above specified equation system and to obtain the unobservable values of A_t and σ_A.

The distance-to-default (DD) can then be obtained with the following formula:

$$DD = \frac{ln\left(\frac{A}{D}\right) + [\mu_A + 0.5\sigma_A]T}{\sigma_A \sqrt{T}} \tag{2.8}$$

Here it needs to be clarified that since μ_A is not observable in this work the assumption will be made that $\mu_A = r$. Even though it is quite restrictive, and definitely not universally applicable, it is commonly used in previous research, giving enough ground for it to be applied here as well (see Nilsson, 2013; Kealhofer, 2003).

Finally, the risk neutral probability that the enterprise will default is effectively the probability that the shareholders will not exercise the call option and buy the assets of the firm for D at maturity. This probability is given by $PD=N(-DD)$.

2.3 Logistic Regression

Financial ratios have been widely exploited by academics in their strive to predict corporate defaults. Beaver (1966) is among the first researchers to apply this methodology. He chose 30 different financial ratios, in an attempt to find which of them have predictive power when it comes to corporate failure, where "failure" is defined as the inability of the organization to fulfill its contractual financial obligations at maturity. A highly important finding related to this academic paper is the fact that Cash Flow to Total Debt is the ratio, which has the largest degree of predictive power when it comes to failure of firms (Beaver, 1966).

Arguably one of the most recognizable papers in the world of corporate finance, when it comes to financial ratios, is the work of Altman (1968). It has served as the foundation of a large number of academic papers, including but not being limited to Deakin (1972), Edmister (1972), Taffler (1982), Goudie (1987), Grice and Ingram (2001) and Agarwal and Taffler (2007). Known as the Z-score, the model is based on a linear combination of five financial ratios, namely Working Capital to Total Assets (TA), Retained Earnings to TA, Earnings Before Interest and Tax to TA, Market Value of Equity to Total Liabilities, and Sales to TA, which are weighted by coefficient estimates based on the sample of 66 defaulted and healthy firms. Originally, the model was applied only on publically traded manufacturing companies, half of which had filed for bankruptcy. The defaulted organizations were then matched with 33 business ventures, which maintained their solvency (Altman, 1968). Finally, it is worth mentioning that subsequently the model has been developed in order to become applicable for both public and private manufacturing and service companies.

Ohlson (1980) made another significant contribution to the empirical analysis dealing with financial ratios via the employment of the logistic regression methodology. In an attempt to overcome the limitations that previous researchers have faced, Ohlson selected nine variables that he deemed helpful in the process of predicting corporate default, without providing theoretical justification in relation to his selection methodology. The author then selected 2000 non-failed and 105 failed US, publically traded corporate entities and applied a logistic function in an attempt to predict their respective failure probabilities. Since a Logit regression was applied, the author argued that he has overcome a number of important restrictive features of previous models, including the assumption of normal distribution and the arbitrary nature of the matching process between healthy and defaulted firms (Ohlson, 1980).

Building on Ohlson's work, Lau (1987) extended the Logit model via the categorization of organizations based on their financial health, ranging from financially stable to fallen into bankruptcy and liquidation. It was then possible to calculate the probability of a firm moving from one category into another, further improving the predictive capabilities of the framework. An additional development in this context was produced by Ameur et. al (2008). The focus of the authors was to determine the variables with the highest explanatory power for a bankruptcy event, and then use them to estimate the default probability for a particular corporation. A large sample of defaulted US companies in the period 1983 to 2002 was chosen. Mimicking the approach taken by a number of other researchers, this study excludes financial service companies, because of the difference they exhibit when compared to organizations from other industries in terms of their structure and bankruptcy environment. All included entities were then classified in relation to the sector in which they operate. The organizations'susceptibility to a bankruptcy event was tested in relation to four standard ratio categories of explanatory variables, namely liquidity, activity, profitability and solidity. In total 34 financial ratios were employed, in order to assess the ability of a firm to service its ongoing expenditure, the efficiency of its asset usage, its short-term operating performance and its long-term solvency. The authors conclude that there are a number of measures with a high degree of relevance in the context of their model, with some of the most important being Working Capital to Total Assets, Cost of Goods Sold to Sales and Net Income to Total Assets (Ameur et. al, 2008).

Considering the fact that the aim of this paper is to calculate company specific PD, the Logit regression methodology can be seen as a suitable alternative testing method. Therefore, the results obtained from the application of this framework will be used as supplementary to those estimated with the Merton model. In addition to the abundant empirical work, which utilizes the logistic regression methodology, Burns and Burns (2008) prove that this method entails fewer assumptions, while remaining statistically robust. Furthermore, this approach exploits the most parsimonious model, while maintaining the ability to identify the belonging of each firm to a specific group (Burns and Burns, 2008). Since in this case the emphasis is placed on distinguishing between healthy and defaulted firms, the Logit regression will be used in order to group all the companies in those two categories.

With the rationale behind the selection of the logistic regression methodology in mind, one can turn to the specifications governing the practical implication of the model. The first step in the methodology is the creation of a dummy variable y, which takes the value of 1 if a company defaults and 0 in case the organization maintains its solvency. A Logit regression is then run, where the dummy variable is chosen as the dependent and all financial ratios considered serve as the independent regressors. The coefficients for each regressor are then obtained and the random variable z_i is created so that,

$$z_i = \sum_{k=1}^{K} \beta_k x_k \tag{2.9}$$

where x is the independent financial ratio, K represents the number of financial ratios, and β is the respective coefficient on each individual ratio. Due to the fact that this is a non-linear model, z_i does not represent the actual PD for each company. PD in this context is given by the (cumulative) logistic probability distribution function,

$$F(z_i) = \frac{1}{1+e^{-z_i}} \tag{2.10}$$

where $F(z_i)$ depicts the probability that the firm will default and e represents the exponential. An advantage of the above specified model is the fact that the obtained default probability estimates can be neither negative nor larger than one, which is of particular use in this context (Brooks, 2008).

The non-linearity of the model has an additional implication. All the β coefficients estimated in (2.9) must be calculated via the usage of maximum likelihood (ML). This is done in order to find the β coefficients that most accurately depict the relationship expressed in the regression equation in relation to the data set being estimated (Frade, 2008). The likelihood function for each observation can then be expressed as:

$$L_i = \left(\frac{1}{1+e^{-z_i}}\right)^{Y_i} X \left(\frac{1}{1+e^{z_i}}\right)^{(1-Y_i)} \tag{2.11}$$

Since all observations are assumed to be independent, the joint likelihood function will simply be the product of all N marginal likelihoods,

$$L(\theta) = \prod_{i=1}^{N} \left(\frac{1}{1+e^{-z_i}}\right)^{Y_i} X \left(\frac{1}{1+e^{z_i}}\right)^{(1-Y_i)} \tag{2.12}$$

Due to the fact that it is easier to maximize an additive function, the natural logarithm of the joint probability for all observations is then taken,

$$LLF = -\sum_{i=1}^{N} \left[y_i \; ln(1+e^{-z_i}) + (1-y_i) \; ln(1+e^{z_i})\right] \tag{2.13}$$

2.4 Receiver-operating characteristic (ROC) curve

Considering the characteristics of the logistic regression and the Merton model, it needs to be stated that both methodologies have certain limitations. The Merton model assumes a constant risk-free rate and a uniform body of corporate debt. Furthermore, the model is usually complex analytically and requires a lot of computations (Wang, 2009). The Logit regression framework on the other hand suffers from the severe disadvantage of being subject to accounting manipulations in the reporting methodology of organizations (Ameur et. al, 2008). Considering these limitations, it is clear that on some instances both frameworks can yield inaccurate conclusions regarding the creditworthiness of some companies. There are two types of errors that can be encountered when using these models:

I. Type I error implies a false prediction of non-default in a case when the firm has actually defaulted, which is known as false non-default.

II. Type II error is related to a false prediction of default, in case the firm has survived and is labeled as false default.

There is a natural trade-off between these two types of errors, depending on the chosen default cutoff. Finally, it is of interest to point out that from the perspective of an investor in the debt obligations of any of the studied entities, Type II error is much more damaging than a Type I.

Since both the Logistic regression and the Merton model are not flawless in their estimations, a technique capable of detecting the presence of Type I and Type II errors in both credit risk assessment procedures must be employed. A perfect alternative can be found in the receiver-operating characteristic (ROC) curve. Originally developed in the 1950s, ROC curves were initially utilized by the field of medicine, where they were used because of their propensity to successfully identify false positive and false negative outcomes of a clinical trial. Since such a facet is applicable in the context of depicting Type I and Type II errors in statistics, the formal statistical testing of the results of the subsequently presented empirical study is made possible. Just like in medical trails, an adequate default model should have the ability to effectively differentiate financially healthy from unhealthy companies. Moody's own quantitative credit risk group was among the first to use this methodology. Baker Stein (2002) postulates that the power of a default model lies in its capacity to account for true defaults and true survivals. Briefly summarized, the ROC curve takes into account the existence of two populations, default and healthy, both of which are plotted against the PD estimates for each individual firm. In this way, the arbitrarily chosen default cutoff point becomes irrelevant, since regardless of where it is actually set, what is important in the above described setting is the fact that some healthy firms will be above it and some defaulted organization will be below it, thus resulting in false defaults and false survivals. The null hypothesis is that if $PD > x$, where x is the randomly selected default threshold, the firm is anticipated to enter bankruptcy. It is therefore extremely straightforward to categorize Type I and Type II errors. The most import output that streams from this methodology is then associated with the specificity and sensitivity of the model, with the former being related to its ability to recognize true defaults and the latter related to the correct documentation of true non-defaults. The ROC curve itself is a visualization of the above depicted testing methodology. The shape of the curve is anticipated to be concave, with a more concave curve characterizing a more powerful model, capable of better predicting defaults. If the model being analyzed is completely unable to distinguish between defaulted and healthy firms, it then produces PD that overlap the default and healthy sample entirely. In such a case the ROC curve is a 45° line. A final alternative is for the ROC curve to be convex, in which case the model predicts lower PD for defaulted than for healthy firms, thus rendering the default risk assessment methodology all but worthless. Finally, a key statistic related to the ROC curve is the area under the curve, known as AUROC. Since the ROC curve is expected to be concave, a high AUROC is associated with a more powerful model (Fabozzi, Chen, Hu, Pan 2010). Finally, using the AUROC value, the Accuracy Ratio (AR) can be calculated in accordance with the work of Engemann, Hayden and Tasche (2003). The authors postulate that,

$$AR = 2A - 1 \tag{2.14}$$

where A is the AUROC. A model can be deemed as a good fit if AR is greater than 0.7.

Chapter 3

Data

The data set, which was selected in the context of both models presented above, consists of 272 healthy companies, trading on the S&P 500 index during the entire course of the sample period from 2006 to 2012. There were no specific criteria applied in the selection process of these organizations, with the sole aim being the selection of solid corporate entities, none of which has defaulted during the entire period of interest. Furthermore, since the S&P 500 is the broadest US based compose, it is ensured that the firms chosen for the study represent a variety of industries, thus arguably increasing the relevance of the subsequently presented results.

The second part of the data set consists of a 56 defaulted US publically listed firms during the period between 2006 and 2012. Information regarding corporate defaults was obtained from reports published by Moody's on annual basis. All the corporations included have been declared bankrupt during the above specified period in accordance with US legislation. There are two types of bankruptcy defined by US law, namely Chapter 7, in which case the firm is liquidated and all of its assets are sold, and Chapter 11, which entails a reorganization of debt obligations and allows firms to proceed with their existence. Thus, even though some of the firms that are listed as defaulted in this study may currently be active, they have formally defaulted at a certain point in time during the sample period.

3.1 Merton Model Data Specifications

In order to successfully implement the Merton model, yearly data regarding the long- and short-term liabilities, along with the number of shares outstanding for all healthy companies at year-end of 2011 were necessary. The same approach was also utilized in the context of all defaulted firms, with the difference being that the data for them was collected one year prior to their default. Additionally, in order to calculate the equity volatility of each organization, daily stock prices were taken and normalized. The value of equity was calculate by multiplying the number of shares with the share price on the last trading day of each year. Since the credit ratings provided by Moody's are forward-looking, implying that they offer guidance regarding the creditworthiness of corporations for a timeframe of at least one year after the rating is issued, a similar approach will be applied when the Merton model is calculated. Therefore, the yearly data on short-and long-term liabilities, along with the value of equity at the end of 2011 will be taken as inputs in the model. Via the usage of Matlab[1], the value of the each company's assets and their volatility will be calculated. Finally, based on the specifications outlined in Section 2.2 *PD* will be obtained for each organization. These default probabilities will be used as guidelines for the likelihood of a company defaulting during the entire 2012, implying that the *PD*s estimated will be used as a forward guidance regarding the financial health of the organizations considered.

3.2 Logistic Regression Data Specifications

When the Logit regression was applied to the previously specified dataset, the methodology that Ameur et. al (2007) used for their research was utilized. As detailed above, 34 financial ratios, grouped in four different categories, will be employed in order to assess the creditworthiness of the companies being considered. The list of the financial ratios is presented in Table A.2 in the Appendix and explores the influence of a large number of accounting figures on the ability of organizations to service their debt obligations. Each ratio is based on yearly accounting data, taken from the accounting statements of all companies included in this empirical research. For each business entity being considered, the ratios were tested for autocorrelation, and the once exhibiting high correlation to a number of other ratios were excluded in an attempt to improve the model. Due to the above described logic governing the credit ratings of Moody's, all of the calculations based on the Logit regression will have a one year predictive capability about the probability of default of a given company. Finally, when the value of the Logit regression is equal to one, the firm in question is expected to experience default in the next 12 months, whereas if the value is equal to zero the firm should be able to maintain its financial health.

[1] The script "Merton Structural Credit Model (Matrixwise Solver)" contributed by Mark Whirdy at Mathworks was applied. Available at http://www.mathworks.se/matlabcentral/fileexchange/39717-merton-structural-credit-model–matrixwise-solver-.

Chapter 4

Results

4.1 Merton Model Accuracy Test

The analysis of the results from the Merton model begins with the reaffirmation that it does not suggest a specific cutoff default point. Therefore, a method capable of determining the presence of Type I and Type II errors is required. As previously specified, a ROC curve provides a good basis for the analysis of the predictive capabilities of a number of frameworks analyzing default risk. Figure 4.1 depicts the actual ROC curve, with detailed information regarding the area under the curve presented in Table 4.1 below. As can be seen from the test results, the utilization of the Merton model can be deemed as warranted in this context. At 0.834 the value of the area under the curve is much higher than the null hypothesis of 0.5, implying that the model has the ability to distinguish between defaulted and healthy firms in most of the instances being studied. This is further proven by the AR value of the model, which in this setting is calculated to be 0.668. The ROC curve, however has no informative properties regarding the nature of the errors that have occurred during the calculation of the Merton model. In other words, it is impossible to distinguish between Type I and Type II errors in this context. Such classification is presented in Table 4.2 below. It is evident that the model struggles with the identification of defaulted companies. Only 25% of the defaulted organizations have been correctly identified, with the other 75% being classified as healthy even though in reality they have defaulted within the next 12 months. This result comes as a clear proof of the difficulty related to correctly assessing default risk, and more importantly in accurately forecasting actual bankruptcies. This notion is further solidified by the fact that 98.3% of the companies that did not default were successfully identified, leaving the Type II errors at just 1.7% of the entire sample. Based on the above presented results, it can be stipulated that in this context the Merton model performs much better at identifying healthy companies, than at recognizing organizations that were about to enter bankruptcy procedures. Even though the former is an integral part of credit risk analysis, as already postulated, investors are much more interested in the adequate prediction of corporate defaults. Based on the results of this empirical study it can then be argued, that while the model has a certain level of capacity to predict corporate defaults, it certainly exhibits limitations when the correct identification of defaulted companies is being considered.

FIGURE 4.1: Merton model ROC Curve

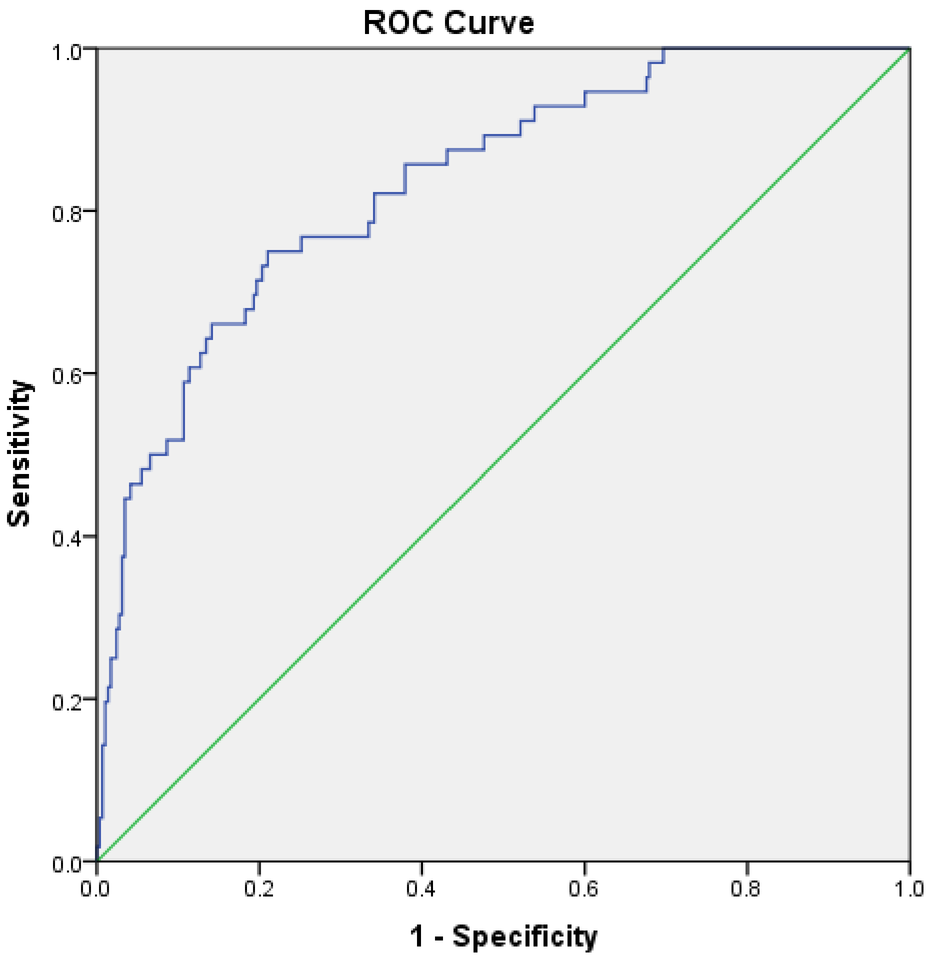


TABLE 4.1: Merton Model Area Under the Curve. Test Result Variables: *PD*

			Asymptotic 95% Confidence Interval	
Area	Std. Error[a]	Asymptotic Sigma[b]	Lower Bound	Upper Bound
0.834	0.029	0.000	0.777	0.891

[a]) Under the nonparametric assumption

[b]) Null hypothesis: true area = 0.5

Table 4.2: Classification of the Merton model

	Predictions		
Dummy	No. of non-defaults	No. of defaults	Overall percentage
0 = Not defaulted	285	5	98.3
1 = Defaulted	42	14	25.0
Total			86.4

The cut value is 0.5

As previously specified, the logistic regression approach was applied on the 56 defaulted companies and on the 272 healthy organizations used in this sample. An approach taken by Ameur et. al (2007) was mimicked, with all of the 34 original accounting ratios being utilized and listed in Table A.3 in the Appendix. Before implementing the actual model it was necessary to check the correlation between the individual ratios and determine which of them were highly correlated with the other explanatory variables of interest. Additionally, the level of significance of each of the variables was then considered, leading to a further exclusion those that had a lower than 90% significance. Therefore, due to high level of correlation and lower than desired level of significance for some financial ratios, the model was executed based on only 24 of the original 34 independent variables being considered. The list of the 24 ratios utilized in this context can be found in Table A.1 in the Appendix.

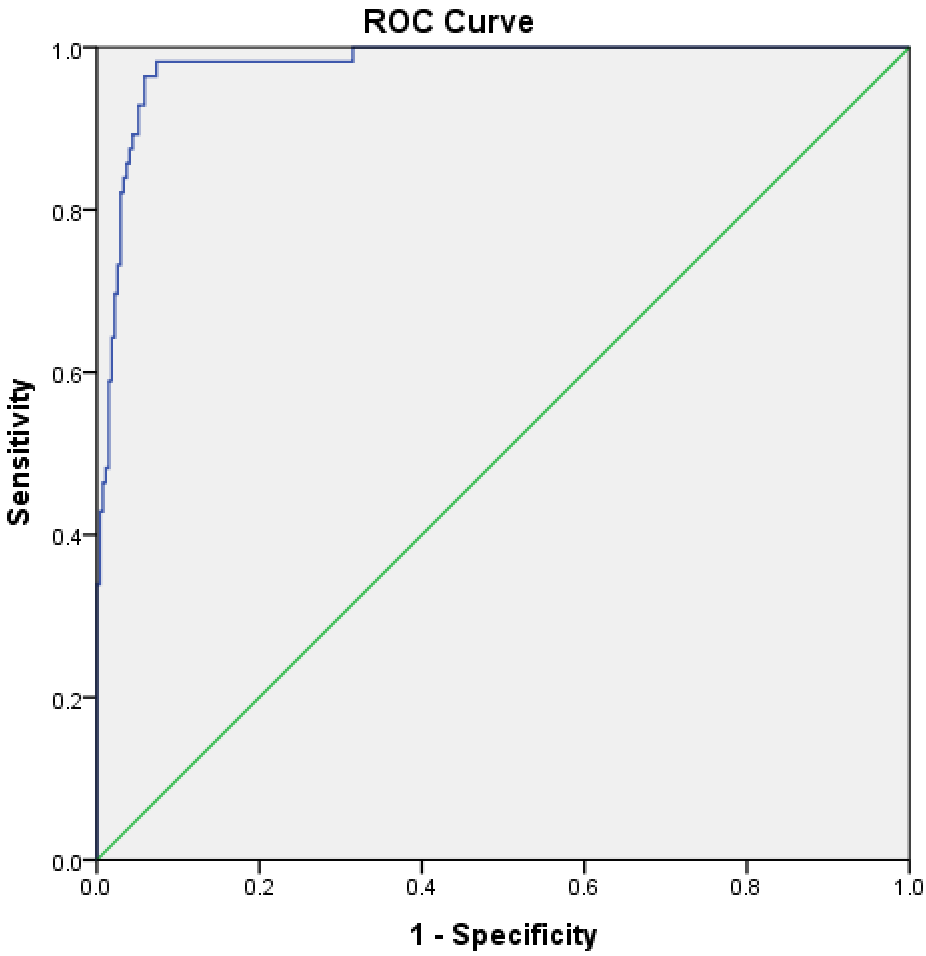
Table 4.3: Classification of the Logistic Regression model

	Predictions		
Dummy	No. of non-defaults	No. of defaults	Overall percentage
0 = Not defaulted	265	8	97.1
1 = Defaulted	15	41	73.2
Total			93.0

The cut value is 0.5

As can be seen from the results presented in Figure 4.2, the logistic regression model exhibits high accuracy in detecting both defaulted and healthy organizations. As already mentioned, the most import output that streams from this methodology is related to the specificity and sensitivity of the model, with the former being related to its ability to identify true defaults and the latter related to the correct assessment of true non-defaults. In this case, 97.1% of all the healthy companies were correctly identified, and additionally 73.2% of all defaulted firms were also accurately assessed. The fact that the logistic regression is characterized by relative low level of Type I and Type II errors, is ascertained by the results of the ROC curve presented in Graph 2. It can then be concluded that the logistic regression is able to quite accurately differentiate between bankrupt and non-bankrupt firms.

FIGURE 4.2: Logistic Regression ROC Curve



4.2 Model Comparison

In this section the two credit risk assessment methodologies employed in this empirical study will be evaluated in relation to the corresponding historic default rates presented by Moody's. The most accurate fashion, in which the evaluation process can be implemented, comes in the form of an individual analysis of the credit risk assessments for every company prepared by the rating agency. Since they are not publicly available, firms will be grouped in relation to their credit rating and the average *PD* for each rating class will be taken into consideration when the accuracy of each methodology is being determined. The analysis will be divided into two parts, related to the two different methodologies employed in this paper. Therefore, a detailed evaluation of the *PD* estimated obtained from the Merton model in the context of the historic default rates presented by Moody's will be offered. This will be done in order to assess the quality of these default probabilities in relation to real world data. The same procedure will then be utilized in relation to the results from the logistic regression.

TABLE 4.4: Merton model *PD* estimates for defaulted firms and historic default rates for Moody's rating classes.

Defaulted companies	**Rating**	***PD* Merton**	**Avg *PD* Merton**	**Avg *PD* Moody's**
Hovnanian Enterprises, Inc.	B1	13.18%		
American Airlines, Inc.	B1	7.68%	10.44%	2.31%
Overseas Shipholding Group, Inc.	B1	6.32%		
Chemtura Corporation, Inc.	B1	14.59%		
Edison Mission Energy	B2	11.01%		
Penson Worldwide, Inc.	B2	9.69%	8.05%	4.73%
U.S. Concrete, Inc.	B2	3.40%		
Tropicana Entertainment, LLC	B2	8.09%		
Midwest Generation, LLC	B3	11.32%		
Dex One Corporation	B3	15.10%		
Aventine Renewable Energy Holdings, Inc.	B3	4.53%	10.25%	7.62%
HLI Operating Company , Inc. (OLD)	B3	8.66%		
Lyondell Chemical Company	B3	11.62%		
American Color Graphics	Caa1	17.46%		
InSight Health Services Corp.	Caa1	4.53%		
Movie Gallery, Inc.	Caa1	5.41%		
Remy International, Inc.	Caa1	2.78%		
Hawaiian Telcom Communications, Inc.	Caa1	9.88%		
Kimball Hill, Inc.	Caa1	11.57%		
Quebecor World, Inc.	Caa1	10.17%		
Vertis, Inc.	Caa1	19.25%		
Building Materials Holding Corporation	Caa1	11.90%		
Builders FirstSource, Inc.	Caa1	12.75%	11.59%	10.23%
Local Insight Regatta Holdings, Inc.	Caa1	12.08%		
Horozin Lines, Inc.	Caa1	4.14%		
Nebraska Book Company, Inc.	Caa1	34.12%		
Aventine Renewable Energy Holdings , Inc.	Caa1	7.62%		
Broadview Networks Holdings , Inc.	Caa1	12.22%		
Global Aviation Holdings, Inc.	Caa1	17.87%		
Houghton Mifflin Harcourt Publish, Inc.	Caa1	13.90%		
James River Coal Company	Caa1	6.59%		
Reddy Ice Holdings, Inc.	Caa1	5.94%		
North Atlantic Holding Company, Inc.	Caa2	31.74%	19.59%	18.50%
Hines Nurseries	Caa2	19.13%		

Leiner Health Products, Inc.	Caa2	32.04%	19.59%	18.50%
Tousa, Inc.	Caa2	17.60%		
Wellman, Inc.	Caa2	21.40%		
BearingPoint, Inc.	Caa2	16.93%		
Milacron, Inc.	Caa2	15.32%		
Ahern Rentals, Inc.	Caa2	12.47%		
Sbarro, Inc.	Caa2	30.01%		
YRC Worldwide, Inc.	Caa2	12.14%		
ATP Oil & Gas Corporation	Caa2	12.51%		
Radio One, Inc.	Caa2	8.74%		
Securus Technologies, Inc.	Caa2	6.22%		
Eastman Kodak Company	Caa2	38.69%		
American Media Operations, Inc.	Caa2	16.36%		
LifeCare Holdings, Inc.	Caa2	22.16%		
Young Broadcasting, Inc.	Caa3	13.82%	28 .33%	29.65%
Circus and Eldorado Joint Venture	Caa3	60.75%		
Mohegan Tribal Gaming Authority	Caa3	8.52%		
Newark Group, Inc.	Caa3	31.66%		
Xerium Technologies, Inc.	Caa3	7.92%		
Ahern Rentals, Inc.	Caa3	37.83%		
Harry & David Holding, Inc.	Caa3	30.82%		
Dune Energy, Inc.	Caa3	35.29%		

Table 4.4 presents the results regarding the defaulted 56 companies, obtained via the application of the Merton model. The final column in the table depicts the historic default rates of the various ratings classes as stated in the annual credit reports published by Moody's. Since the rating agency does not offer specific *PD* figures in its credit assessments, historic default rates can arguably be deemed as a reasonable metric for bankruptcy risk. A good starting point would be to state that on a number of instances the model presents default probabilities that are rather low, especially considering that the companies in question are so close to default. There are multiple firms with *PD* estimates lower than 10%, with US Concrete, Inc. and Remy International, Inc. having *PD* values of 3.4% and 2.78% respectively. Such low estimates certainly strengthen the conclusion drawn in Section 4.1 regarding the relative inability of the Merton model to accurately identify true defaults. With that said, the emphasis can now be shifted to the comparison of the historic default probability associated with a specific rating class presented by Moody's with the corresponding average *PD* obtained via the Merton model. As can be seen from the table, the Merton model performs much better when firms enjoying a higher credit rating are being considered. When rating classes rated between B1 and B3 are being evaluated, it is apparent that the Merton model is more conservative in its credit risk assessment. A similar conclusion can be drawn when organizations rated Caa1 are examined. In this context however, the difference between the two is much smaller. When it comes to

businesses rated Caa2, the difference in *PD* is much lower, and for ventures with a rating of Caa3 the *PD* estimates given by the Merton model are in fact lower than the historic default rates observed by Moody's. It can therefore be argued that due to the size of the sample and the fact that all the companies being considered have actually defaulted, the larger default probabilities calculated via the Merton model can simply be a result of a selection bias. Since only defaulted companies are considered, the Merton model is able to yield higher *PD* for higher rated companies due to their lack of financial strength. One must then raise the question why was the credit rating of these organizations so much higher than their default risk suggested by the rather straightforward structural model utilized in this study. In can then be concluded that in this context Moody's was rather slow in adjusting its risk assessment firms that were so close to defaulting.

With the analysis regarding the defaulted companies completed, the attention can now be turned to Table 4.6, presenting the *PD* estimates of the Merton model for the healthy companies in this sample. Based on the results listed in the table, it can be claimed that for most ratings classes the Merton model overestimates default probabilities. This observation is particularly apparent in the context of companies with very high credit ratings. Organization rated Aaa, Aa1, Aa2 experience 0% historic default rates, yet the model calculates their *PD* to be considerably higher. A similar conclusion can be drawn regarding firms with credit ratings from A1 to Ba2. However, when lower rated business entities are evaluated, the Merton model's *PD* computations are much more in line with historic default rates. On most of these instances, excluding the case of the sole healthy company rated Caa1, the model is still conservative when compared with historic default rates. With that said, this feature is much less pronounced in this case and the discrepancy between the two metrics is much smaller than for higher rated companies. However, when the results of the ROC curve methodology and the *PD* estimates for defaulted firms are incorporated in this context, it is impossible to unequivocally claim that the Merton model offers categorical improvement on the methodology utilized by Moody's.

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instances, excluding the case of the sole healthy company rated Caa1, the model is still conservative when compared with historic default rates. With that said, this feature is much less pronounced in this case and the discrepancy between the two metrics is much smaller than for higher rated companies. However, when the results of the ROC curve methodology and the *PD* estimates for defaulted firms are incorporated in this context, it is impossible to unequivocally claim that the Merton model offers categorical improvement on the methodology utilized by Moody's.

TABLE 4.6: Merton model *PD* estimates for healthy firms and historic default rates for Moody's rating classes

Healthy companies			
Credit rating	Number of companies	Average *PD* Merton	Average *PD* Moody's
Aaa	2	3.09%	0.00%
Aa1	1	5.38%	0.00%
Aa2	2	2.11%	0.00%
Aa3	5	3.86%	0.11%
A1	8	4.24%	0.06%
A2	29	4.20%	0.03%
A3	24	3.80%	0.04%
Baa1	40	4.47%	0.13%
Baa2	49	4.25%	0.14%
Baa3	52	4.50%	0.35%
Ba1	18	4.86%	0.67%
Ba2	7	2.90%	0.59%
Ba3	14	4.62%	1.95%
B1	9	4.54%	2.31%
B2	6	5.99%	4.73%
B3	5	7.60%	7.62%
Caa1	1	7.94%	10.23%

With the results regarding the Merton model in mind, the analysis can now be focused to the Logit regression *PD* estimates. The resulting *PD* estimates for the defaulted companies are presented in Table 4.7. The *PD* calculated with the logistic regression will again be compared with the actual historic default rates for the corresponding rating class. Unlike the Merton model, the logistic regression yields extremely high default probabilities for all firms being considered. In this setting however, this is arguably desirable. Since the aim is to minimize the existence of Type I errors, it is quite advantageous that the model predicts such high possibility of bankruptcy for all the defaulted organizations. On the other hand, the model's computations are much higher than the historic default rates for the different ratings classes. As previously stated however, Moody's was unable to adjust its credit ratings with the necessary urgency in this particular context. This can then lead to the conclusion that the relative conservativeness of the Logit regression approach is warranted.

TABLE 4.7: Logistic Regression *PD* estimates for defaulted firms and historic default rates for Moody's rating classes

Defaulted companies			
Credit rating	Number of companies	Average *PD* Logistic	Average *PD* Moody's
B1	4	91.95%	2.31%
B2	4	76.70%	4.73%
B3	5	84.65%	7.62%
Caa1	19	92.78%	10.23%
Caa2	16	89.53%	18.50%
Caa3	8	90.01%	29.65%

TABLE 4.8: Logistic Regression *PD* estimates for healthy firms and historic default rates for Moody's rating classes

Defaulted companies			
Credit rating	Number of companies	Average *PD* Logistic	Average *PD* Moody's
Aaa	2	27.90%	0.00%
Aa1	1	59.95%	0.00%
Aa2	2	15.38%	0.00%
Aa3	5	36.51%	0.11%
A1	8	38.67%	0.06%
A2	29	25.35%	0.03%
A3	24	26.26%	0.04%
Baa1	40	36.25%	0.13%
Baa2	49	35.15%	0.14%
Baa3	52	30.20%	0.35%
Ba1	18	29.12%	0.67%
Ba2	7	29.53%	0.59%
Ba3	14	36.43%	1.95%
B1	9	46.40%	2.31%
B2	6	18.88%	4.73%
B3	5	31.73%	7.62%
Caa1	1	57.02%	10.23%

When the attention is turned to Table 4.8, presenting the *PD* estimates from the logistic regression for the healthy companies, there are a number of issues that require consideration. First and foremost, it needs to be underscored that the average default probabilities obtained from the logistic regression are much higher across all rating classes, when compared with the historic default rates presented by Moody's. Even though there are only two companies having the highest Aaa rating in this study, it is quit shocking to see that their average *PD* can be as high as 27.9%. Such companies are expected to have extremely low default risk and the default probabilities obtained from the Logit regression can arguably be deemed as unreasonably high. A similar conclusion can be reached when it comes to organizations rated Aa1, Aa2, Aa3. The picture does not change for organizations with lower ratings either, with the logistic regression grossly overestimating their *PD* in comparison to actual observed historic default rates. It can therefore be concluded that the Logit regression is performing quite poorly, when it comes to the healthy companies in the context of this particular data set. With that in mind, it is vital to reiterate that the methodology was concluded to be able to accurately identify healthy businesses 97.1% of the time. A limitation in the ROC curve methodology can then be pointed. Since, as already shown, the logistic regression is very conservative in its *PD* estimates for defaulted companies, it is possible that the cutoff default point is selected so high, that organizations with *PD* of 30% or even higher can be identified as healthy. When being mindful of the fact that only companies with the lowest possible credit rating exhibit historic default rates with such frequency, it then becomes apparent that the *PD* computations obtained from the logistic regression are arguably unrealistic. Even though the model theoretically works and fulfils the ROC curve test, the resulting *PD* estimates for the healthy companies lead to the conclusion that with this particular data set, the Logit regression is overly conservative and enjoys little real world implications.

Chapter 5

Conclusion

This paper utilized a sample of 272 healthy companies and 56 defaulted organization in an attempt to evaluate the ability of the Logit regression framework and the Merton model to correctly predict corporate defaults. Additionally, the default probabilities obtained from the aforementioned methodologies were compared to the corresponding rating class historic default rates presented by Moody's.

The Merton model was able to successfully classify only 25% of the defaulted companies and 98.3% of the healthy organizations. As far as bankrupt business entities are concerned, the model significantly underperformed the Logistic regression, which correctly identified 73.2% of the defaulted firms. Furthermore, the logistic regression accurately recognized 97.1% of the healthy companies, thus clearly offering superior performance in relation to its ability to distinguish between defaulted and healthy organizations.

With that said, the Logistic regression yielded very conservative *PD* estimates for both healthy and defaulted organizations. In the context of the latter this can be deemed advantageous, since all of the organization included in this group defaulted within the next 12 months. The default probabilities for the healthy firms were however overly cautious, especially when compared to the corresponding rating class historic default rates presented by Moody's. It can therefore be concluded that even though the Logistic regression was more successful at recognizing defaulted companies, the *PD* estimates offered by this methodology were overly conservative and thus have little real world implications.

The Merton model offered *PD* estimates that were much more in line with historic default rates. The framework was more conservative only in relation to higher ratings classes, and even in this context was much closer to actual observed default rates than the Logistic regression. The model however offered lackluster performance when the actual identification of defaulted corporations is concerned, making it impossible to claim that it yielded superior results than the logistic regression. With one model being overly conservative and the other not conservative enough, it can only be concluded that the point of default it extremely difficult to pinpoint, thus leaving an appealing opportunity for future research, in the continuous strive to improve the accuracy of the existing credit risk assessment methods.

Appendix A

Appendix

A.1 Tables

Table A.1: SPSS Output for Logistic Regression

Ratio	Coefficient
Current Assets/Current Liabilities	4.862
Cash/Current Liabilities	17.290
Cash/Total Assets	-24.523
Cash Flow/Current Liabilities	-79.937
Cash Flow/Total Debt	392.707
Current Liabilities/Equity	-2.559
Current Assets/Total Debt	-36.398
Quick Assets/Current Liabilities	-6.351
Quick Assets/Inventories	-1.302
Working Capital/Total Assets	-7.930
Working Capital/Sales	2.904
Inventories/Sales	-29.484
Accounts Receivable/Sales	-15.808
AR/Inventories	-0.120
COGs/Inventories	0.999
COGs/Sales	-27.333
NI/Total Assets	-184.095
NI/Equity	-1.842
NI/Sales	12.781
Retained Earnings/Total Assets	2.934
EBIT/Invested Capital	-.080
EBIT/Total Assets	6.102
EBIT/Sales	-58.357
Sales/Total Assets	68.651

TABLE A.2: Moody 's Global Corporate Average Cumulative Default Rates (%, 1981–2013)

Rating	Time Horizon									
	1	2	3	4	5	6	7	8	9	10
Aaa	0.00	0.03	0.13	0.24	0.35	0.47	0.53	0.62	0.68	0.74
Aa1	0.00	0.06	0.06	0.11	0.17	0.24	0.30	0.36	0.43	0.50
Aa2	0.02	0.03	0.06	0.23	0.38	0.51	0.65	0.78	0.88	0.99
Aa3	0.03	0.10	0.20	0.29	0.39	0.50	0.59	0.65	0.72	0.79
A1	0.06	0.11	0.24	0.40	0.53	0.64	0.78	0.93	1.10	1.29
A2	0.07	0.17	0.27	0.42	0.57	0.78	0.99	1.18	1.42	1.69
A3	0.08	0.20	0.34	0.48	0.69	0.91	1.20	1.42	1.59	1.74
Baa1	0.14	0.38	0.66	0.95	1.27	1.62	1.86	2.21	2.45	2.73
Baa2	0.20	0.51	0.80	1.24	1.69	2.12	2.55	2.98	3.44	3.91
Baa3	0.32	0.97	1.73	2.63	3.51	4.30	5.03	5.71	6.27	6.84
Ba1	0.43	1.50	2.35	3.47	4.56	5.66	6.61	7.31	8.19	9.05
Ba2	0.68	0.21	4.07	5.92	7.66	9.12	10.45	11.54	12.54	13.39
Ba3	1.13	3.47	5.91	8.26	10.33	12.40	14.10	15.75	17.15	18.33
B1	2.31	6.26	10.15	13.52	16.05	18.02	19.82	21.43	22.84	24.25
B2	4.73	10.55	15.19	18.51	21.02	23.39	24.79	25.84	26.79	27.67
B3	7.62	15.37	20.55	24.12	26.93	28.98	30.64	31.65	32.32	32.94
Caa1	10.23	21.64	31.63	39.74	47.15	52.80	55.63	59.26	64.13	70.15
Caa2	18.50	30.85	40.30	47.36	52.68	56.42	58.90	61.56	61.56	61.56
Caa3	29.65	44.35	54.07	61.12	67.61	69.03	70.95	70.95	70.95	70.95
Ca–c	41.18	54.85	65.30	70.93	74.50	74.73	74.73	74.73	74.73	74.73
Investment Grade	0.13	0.34	0.58	0.82	1.10	1.37	1.68	2.07	2.53	3.14
Speculative Grade	5.12	10.64	15.92	20.37	23.86	26.86	29.52	32.34	35.43	38.65
All rated	2.10	4.13	6.08	7.65	8.86	9.87	10.72	11.71	12.73	13.88

Table A.3: Classification of Financial Ratios by Ameur et. al (2007)

Liquidity	Activity	Profitability	Solidity	Others	
$\frac{CurrentAssets}{CurrentLiabilities}$	$\frac{Inventories}{Sales}$	$\frac{NetIncome(NI)}{TotalAssets}$	$\frac{TotalLiabilities}{TotalAssets}$	Log (Market Equity)	
$\frac{Cash}{CurrentLiabilities}$	$\frac{AccountsReceivables}{Sales}$		$\frac{NI}{Equity}$	$\frac{Equity}{FixedAssets}$	Number of Employees
$\frac{Cash}{TotalAssets}$	$\frac{AR}{Inventories}$	$\frac{NI}{Sales}$	$\frac{MarketEquity}{TotalLiabilities}$	Dummy variables by industry	
$\frac{CashFlow}{CurrentLiabilities}$	$\frac{COGs}{Inventories}$	$\frac{RetainedEarnings}{Assets}$	$\frac{TotalDebt}{TotalAssets}$		
$\frac{CashFlow}{TotalDebt}$	$\frac{COGs}{Sales}$	$\frac{EBIT}{InvestedCapital}$	$\frac{TotalDebt}{Stockholder'sEquity}$		
$\frac{CurrentLiabilities}{Stockholder'sEquity}$		$\frac{EBIT}{Assets}$	$\frac{MarketEquity}{TotalDebt}$		
$\frac{CurrentAssets}{TotalDebt}$		$\frac{EBIT}{Sales}$	$\frac{EBIT}{InterestRateExpenses}$	$\frac{COGs}{Sales}$	
$\frac{QuickAssets}{CurrentLiabilities}$		$\frac{Sales}{Assets}$			
$\frac{QuickAssets}{Inventories}$		$\frac{Sales}{TotalDebt}$			
$\frac{WorkingCapital}{TotalAssets}$		$\frac{DividendsPerShare}{Price}$			
		$\frac{EPS}{Sales}$			
		$\frac{Price}{EPS}$			

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