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Rating changes

Can they be predicted with the Merton model?

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Abstract

Title	Rating changes - Can they be predicted?
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Five key words	The Merton model, credit risk, credit rating, rating changes, rating prediction
Purpose	The purpose was to investigate if the Merton model had any predictive power of changes in Moody's credit ratings and if there was a difference in the predictability between upgrades and downgrades. This was done in an effort to either support or dismiss the opinion that credit ratings are lagging.
Methodology	The distance-to-default (DD) was calculated with the Merton model. The DD's and the credit ratings were run in logit regressions.
Theoretical perspectives	The Merton model by Robert C. Merton (1974) which is based upon the work by Black and Scholes (1973).
Empirical foundation	A sample of 100 American, non-financial public companies constituted the foundation for the study.
Conclusions	Some evidence for that credit ratings are lagging was found. The Merton model had some predictive power of rating changes, especially for downgrades.

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1. Prelude

This section aims to introduce the reader to the subject as well as to present some background information to the problem which constitutes the base for this thesis. Also the purpose, delimitations and considered audience will be presented in this introductory part.

1.1 Introduction

For a very long time credit ratings were considered more of an art rather than a science. But in the 1990s quantitative models that measure absolute credit risk started to gain popularity by practitioners. With the quantitative models it became possible to measure the absolute credit risk i.e. to say that a firm has a certain probability to go bankrupt within a certain time frame. Until then, the credit rating agencies had used a more qualitative approach in which the analysts' understanding of the company and the industry resulted in an opinion of the creditworthiness of the firm. The introduction of quantitative models influenced the rating industry and new firms such as the KMV Corporation (later bought by Moody's) that used quantitative models entered the market.

Even with the entrance of firms that use quantitative models to measure credit risk the large traditional firms Moody's, Standard & Poor's and Fitch have maintained their dominance on the market. Today almost all actors that want to issue securities on the market need to have a credit rating. The credit rating agencies are assessing the creditworthiness of firms, countries and all kind of financial assets. A rating is assigned to each rated object and represents the object's ability to fulfill its payments. The assigned credit ratings can therefore have a huge impact on what kind of terms creditors are willing to give to debtors when lending them money.

The rating agencies fill an important function in the financial sector since large borrowers such as international corporations or countries require advanced and heavy analysis before an adequate credit rating can be obtained. Banks and creditors but foremost private investors, need the rating agencies' opinion on the investments they are about to make since they lack the resources and the knowledge to do it themselves.

With this important role comes a lot of responsibility for the functioning of the financial sector and in extension the society at large that relies heavily on the assumption that the credit ratings are timely and correct. When this is not the case it has a huge impact on the financial sector as well as the society. Scandals like Enron or the latest financial crisis is recent evidence of the non-infallibility of the rating agencies.

These scandals and the inability of the rating agencies to timely rate firms have raised a lot of criticism and questions. Among the raised questions are whether or not there is a lag in the credit rating of firms since the rating process is rather slow and the assigned ratings do not always tend to actually be the correct one.

There have been a lot of attempts to spot and measure lags using different kind of models. Most studies have used models that use market data. The existence of a lag has been confirmed in several cases and the studies also show that it is easier to predict rating downgrades than rating upgrades. On the contrary, event studies of price reactions to rating changes indicate that the predictability would be the opposite. That market based models would be better to predict upgrades than downgrades.

If there is a lag in the credit ratings by the rating agencies it could have several implications on the financial system, it should therefore be of great value to try to clarify this. Further on the ambiguity about the asymmetry in the prediction ability by the Merton model should be interesting and worthwhile to sort out.

1.2 Purpose

The purpose of this thesis is to investigate if the Merton model, which is a quantitative and objective model, have any predictive power of changes in Moody’s credit ratings. This is done in an effort to either support or dismiss the opinion that the credit ratings are lagging. The purpose is also to test if the there is an asymmetry in the Merton model's ability to predict either upgrades or downgrades.

1.3 Delimitations

The thesis is limited to only investigate the prediction capability of the Merton model and will not regard other credit risk models. The sample of companies and ratings for this thesis is limited to large, American, non-financial firms due to the restricted time frame as well as limited sources of information for other kind of firms. The reasons for not including financial firms are that the calculations will be somewhat more complicated due to the big differences in the capital structure of financial firms; they also make the comparison to other firms harder since financial firms are unique in several ways.

The study covers seven years that roughly captures a whole economic cycle with both good and bad years in the economy. The chosen time frame starts in 2003 and ends in 2009, which is when the National bureau of economic research concluded that the recession had ended. (National Bureau of Economic Research, 2010)

1.4 Target audience

Foremost this thesis is aimed at finance students with an interest in credit ratings and credit risk but participants on the credit market and financial researchers could also benefit from the thesis.

1.5 Thesis outline

The following section will present facts regarding the theory of credit risk, credit rating and the Merton model as well as previous research. The hypotheses will also be presented in the next section. Thereafter section 3 will explain the methodology used throughout the thesis. Section 3 will also outline what kind of simplifications that has been made as well as how the financial data has been retrieved. The results from the data collection and the testing of the data in the sample with regression analyses will be presented in section 4. This section will also present the results discussion. Finally section 5 will conclude the findings and present suggestions for future research.

2. Theory and previous research

This section will present the theoretical framework for the rest of our thesis and also describe the rating process and different credit risk models. Previous research and studies will also be presented to the reader to provide a picture of what has been made earlier and what this thesis can provide for the future. Finally the hypotheses will be presented.

2.1 What is credit risk?

"...credit risk in a narrow sense can be defined as the risk arising from an unexpected deterioration in the credit quality of a counterparty..."(Saita, 2007)

Just as the quotation above says, the credit risk is the probability that a counterpart is not able to fulfill its commitments to fully pay its promised principals and interests on time or at all. That counterpart could be any kind of entity that has issued securities on the market.

The creditor protects itself from the default risk by charging a premium over the risk-free rate, the credit spread, which is proportional to the firm's default probability. The amount of risk that a creditor can bear depends on the loss in the event of default and it can vary between the different debt securities of a firm. A senior claim has a higher recovery rate than a junior claim and it is therefore important for a security holder to not only be informed about the default probability but also about the seniority of the claim. Only the default probability will be used in this thesis. The credit risk reflects the issuer's default probability and not specific issues, therefore the recovery rate is not considered further in this thesis.

To be very precise the bond rating reflects the quality of specific issues and not the quality of the issuer. But in practice the rating is used to describe the creditworthiness of the issuer. This simplification is reasonable since it is very rare that the credit rating of different issues of the same issuer have different ratings. Even the rating agencies do not distinguish between different issues and issuers. They usually refer to the whole company in their ratings. (Hull et al., 2004) In this thesis the same approach to credit rating is taken which means that the credit rating reflects the whole company. The default is therefore seen in both the rating and the Merton model's distance-to-default (DD) as a company-wide event and not isolated to a specific bond issue.

2.2 Development of credit risk measures

The credit rating agencies developed the traditional way to assess credit risk. It is based on the subjective judgment of an analyst based on both quantitative and qualitative aspects. This analysis results in an opinion of the creditworthiness of the issuer. The opinion is expressed as a letter and/or number on an ordinal scale that describes the relative creditworthiness; A is better than B and so forth. The credit rating reflects the long term ability of the issuer to fulfill its debt obligations throughout a whole business cycle.

The quantitative analysis is mainly based on financial reports and market data of a company. The qualitative analysis is the part that differs most from the quantitative models. It studies soft issues that are harder to put a certain number to, such as the ability of the management, the competitiveness in the industry and the characteristics of the industry such as growth and sensitivity to technological change. The analysts work closely with the issuer and have access to disclosed information about the company. With other words, there is a lot of information incorporated in a credit rating and this should be emphasized so that the reader do not get the impression that the Merton model measure of credit risk is precisely the same as the credit rating agencies' measures.

An early attempt to create a quantitative model to measure credit risk was to use different accounting ratios such as the leverage ratio to predict the probability of default. The leverage ratio for example has a positive correlation with the credit risk. An increase in leverage will also increase the credit risk. This and other accounting ratios related to bankruptcy prediction were used by Altman (1968) when he developed his "Z-score model". A number of financial ratios were chosen and weights were added to the ratios to get the "Z-score". A lower score predicted higher probability of bankruptcy and vice verse.

The ratios and weights were chosen based on historical financial data from a sample with bankrupt companies and a sample with non-bankrupt companies that were similar to the companies that had gone bankrupt. This model made it possible to discriminate bad firms from good ones in a more objective way compared to the traditional expert opinion. The Z-sore model has been further developed by Altman and other researchers with different ratios and weights.

Some criticism has been raised regarding these kinds of models. The main criticism is the exclusive use of accounting data which is only available in discrete intervals (usually once a year) which make the model insensible to fast moving changes in borrowers' condition. The models have also been criticized for their weak theoretical foundation. They are based on historical events and data mining and the forward looking abilities are limited to the assumption that the characteristics of bankrupt firms in the past will be the same in the future. (Altman and Saunders, 1997) Empirically accounting based models have also shown to have less explanatory value than market based models. (Tanthanongsakkun and Treepongkaruna, 2008)

In the beginning of the 70's theories that suggested the use of market data to measure credit risk were presented. In 1974 the Merton model made its entrance to the credit risk market. (Merton, 1974) The Merton model uses both market data and accounting data. Market prices and price changes which reflect the investors view of the future pay-off of a company make the model sensible to changes in the market. The model is able to measure absolute credit risk instead of assigning a score based on characteristics of bankrupt firms and with the combination of accounting data and market data the model is more objective and forward looking than previous credit risk models. The basic idea of the model is that a firm goes into default when the market value of its assets falls below its debt obligations and that the probability of the default event can be calculated. The Merton model was quickly adopted and made popular among researchers and it is the Merton model that will be used in this thesis.

2.3 Moody’s and the credit rating process

Today the credit rating market is highly consolidated and the two largest credit rating agencies, Moody’s and Standard & Poor’s, have about 80% of the market. (Hill, 2002) The rating process of S&P and Moody's is similar but this section will only describe the rating process of Moody’s since that is the source of the actual credit ratings used in this thesis.

The objective of a credit rating is to determine whether or not an issuer will be able to serve its principal and interest payments in the future. An extensive analysis of an issuer’s background and its future together with opinions regarding the industry as a whole and the macro financial outlook constitutes a large part of the foundation for a credit rating. But it is not all about the numbers, soft values such as the track record of the management and the issuers own opinion about the future is also important parts for a credit rating agency when determining upon a certain rating. The final rating is determined by a rating committee whom are presented with all these variables and facts by the lead analyst of the specific case. (Moody's Inc., 2012)

The rating process takes between 60 to 90 days to perform and generally begins with that an issuer contacts Moody’s to order a credit rating. From there a team of analysts starts the process by meeting the client. After the initial meeting the analysts work with financial data, macro financial information etc., to achieve a fair economic view of the issuer. During that period contacts with the issuer can be made in order to ask follow-up questions and to clarify issues that might turn up. When the analysis is completed by the team the lead analyst present the findings and a recommendation to a confidential rating committee that will decide upon the final credit rating. After that the rating is presented to the issuer that have a possibility to object if they do not approve and perhaps explain certain issues in more depth. Then the credit rating is published through Moody’s website as well as with a public announcement. Now the rating process is done but Moody’s still keep a steady eye on the issuer and continuously analyze new statements and fluctuations in the world economy and if necessary downgrade or upgrade the given credit rating. Opinions and outlooks of the issuer will also be published by Moody’s on a continuous basis.

2.3.1 Moody's acquisition of the KMV Corporation

In 2003 the KMV Corporation now known as Moody's Analytics where bought by Moody's. (Moody's Inc., 2010) KMV developed and commercialized the Merton model with their empirically observed Expected Default Frequency (EDF). The main difference between the KMV version of the Merton model and the original version is the EDF distribution since the Merton model uses a normal distribution instead. The EDF distribution is an empirically observed default distribution constructed by the KMV Corporation based on a large number of bankrupt companies. The Merton model in this context is known as the KMV model.

If the EDF measure has a substantial weight in Moody's rating process, it would indicate a potentially high correlation with the measure calculated using the Merton model. But how the takeover of KMV has affected the rating process is not public information and is very hard to say. What is certain is that Moody's Analytics Inc. is separate from Moody's Investor Service but there might still be a possibility that the KMV model is used as a part of the rating process and not only as a supplementary measure. Even if the KMV model is used by Moody's in their rating process, their process considers far more than just the probability of default given by the KMV-model. Therefore it is not likely that the rating process is affected by the EDF in a substantial way.

2.3.2 Reasons for differences in the DD and the actual credit rating

There are several differences between the Merton model's DD and the actual credit rating that is given by rating agencies. Several differences has been mentioned throughout the thesis so far but what is important to further emphasize is the fact that the rating agencies has access to inside information and financial data that is not disclosed to other actors on the market in the same extent. Both the Merton model and Moody's for instance have the same objective, to measure credit risk. But since the Merton model only relies on publicly available data it can never incorporate the same amount of information and reflect the firm's reality as the credit rating given by Moody's.

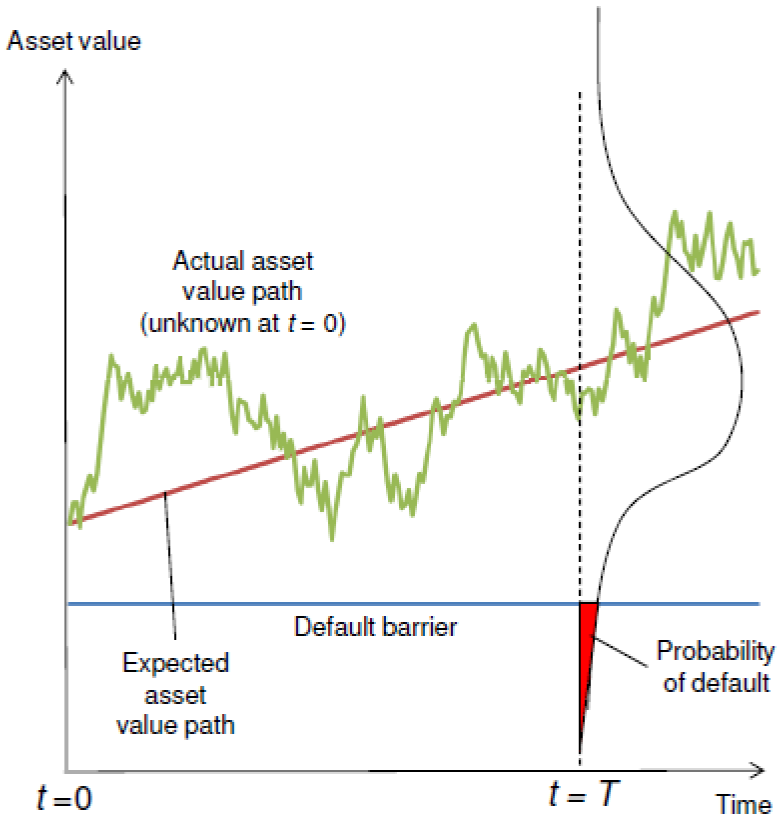
The use of inside information allows Moody's to anticipate the future of a specific firm and can for this reason also predict a firm's future financial health and ability to serve its financial obligations. The Merton model relies directly on market data and since the Merton model does not take the same time to calculate as a whole rating process does it can also be much quicker in adjusting its "rating" of a firm due to changed conditions. Though, again, the rating by the rating agencies should not switch too fast since it should be long term and very stable.

2.4 The Merton model

The option pricing theory of Black and Scholes (1973) is the foundation of the Merton model. (See appendix 1 for the underlying mathematical formulas.) The Merton model developed by Robert C. Merton in 1974 uses the option pricing theories assumptions and theoretical framework to measure credit risk. (Merton, 1974) In the Merton model, the value of equity is viewed as a call option on the assets of a firm. In the same way the value of debt is also dependent on the value of a firm's assets. Thus, the liabilities and the equity of a firm are seen as contingent claims. The equity is a residual claim so its market value depends on the probability that the value of assets exceeds the liabilities. The value of debt is a fixed claim so its market value can never be greater than the face value. There is always a risk that the asset value falls below the face value of debt which reduces the market value of debt. When the face value of the liabilities is greater than the value of the assets the company is in default and the probability that a company will default in the future is its credit risk.

The version of the Merton model used in the thesis is largely taken from Crouhy et al. (2000). The graph below graphically illustrates the basics behind the Merton model and how the credit risk is calculated.

Graph 1.



Graph 1 shows the y-axis that measures asset value and the x-axis that measures time. The time term that is usually used is one year. If the chart is read chronologically from the left to the right it starts with two intercepts in the y-axis. The red one is the asset value which is calculated by adding the market value of equity to the market value of debt. The blue one is the default barrier that is calculated by the principals and interests that are due within one year. The expected value line illustrated by a red line is calculated by adding the expected growth to the asset value at time t. The actual asset path illustrated by a green line (one of an infinite number) is unknown at time t but by assuming a log normal distribution of the asset value the probability of default at time T can be predicted by calculating the number of standard deviations between the expected asset value and the default barrier at time T. The part of the normal distribution (the red area) that falls below the default barrier constitutes the probability of default - the credit risk. When the distance between the asset value and the default barrier decreases the expected asset value approaches the default barrier and the credit risk increases. The same thing happens when the asset growth decreases. The credit risk also increases when the asset volatility increases since it increases the probability that the asset value falls below the barrier.

Presented below is the mathematical formula for the Merton model that we will use through this thesis:

$$DD = \frac{\ln\left(\frac{A_0}{B}\right) + \left(\mu - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{1}$$

Interpretation of the Merton equation:

A_0 = Asset value at time zero

B = Distress barrier

μ = Asset growth (risk free rate)

σ = Asset volatility

T = Time horizon until expiration

How the individual parameters in the calculation has been retrieved and simplified is explained in more detail later in the methodology section.

2.5 Problem discussion, previous research and hypotheses

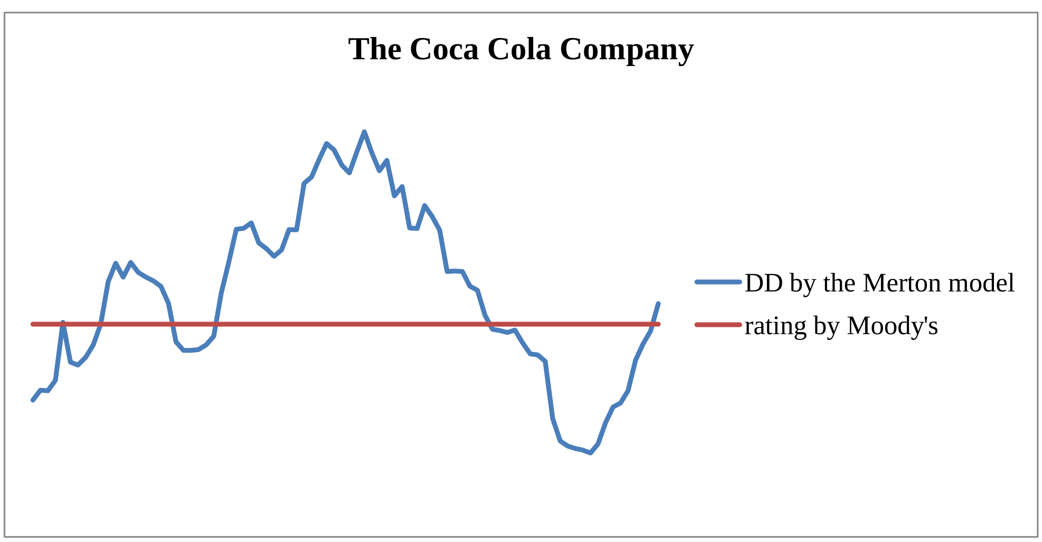
Both the credit rating assigned by Moody's and the credit risk measured by the Merton model measure the probability of default. This would indicate that the measures would be similar, but still they differ in various ways. An important difference is that the credit rating should reflect the credit risk throughout the whole business cycle and are meant to be long term. Therefore they do not take into consideration temporary fluctuations in the creditworthiness.

A change in the bond market value in the short run, that does not fundamentally affect the probability of the full repayment at maturity, will not cause any rating changes. This means that a company with a credit rating that experiences a dip in its financial strength will not be downgraded if the downturn is considered only temporary and not big enough to make a significant impact on the whole business cycle.

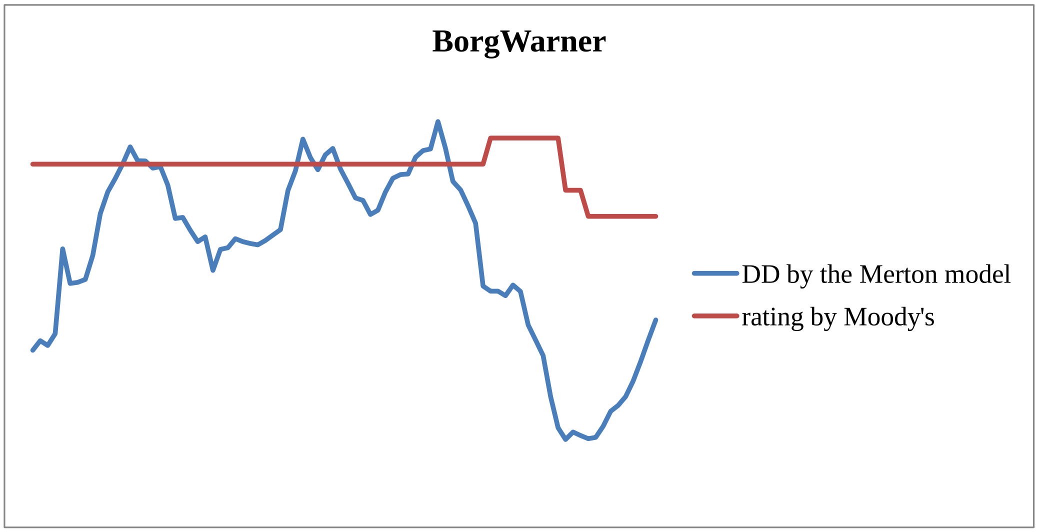
On the contrary the Merton model responds immediately to such changes by increased volatility in equity prices and decreased market capitalization. Apart from being more volatile, the Merton model is also procyclical since it uses market values that increases in good times and decreases in economical downturns.

The credit rating agencies claim that the credit ratings should be insulated from these cyclical changes. This is something that has been confirmed by Amato and Furfine (2004) when they tested if the ratings of US companies were procyclical and they found that they were not. Both the long term perspective and the non procyclicality makes the credit rating stickier compared to a purely quantitative model such as the Merton model. This is illustrated by the graphs below:

Graph 2: The Coca Cola Company



Graph 3: BorgWarner



In graph 2 and 3 the scale and the descriptions on the y-axis are not shown since the charts are only meant to show the relative differences. The x-axis covers the chosen time frame in the thesis. The main difference is that the Merton model changes often and much and that the credit rating is more stable.

Even though or maybe because of the fact that the DD of the Merton model changes continuously there have been suggestions that the model is able to pick up early changes in the creditworthiness of an issuer. The idea is that the Merton model, since it quickly picks up changes in the market, is able to predict changes in the credit rating. The Merton model's forecasting ability is explained by the fact that the capital market and especially the equity market is fairly efficient and liquid. The equity holders have strong incentives to collect and evaluate data to assess the risk connected to their investment. Any change in the opinion of the investors changes the market prices. The signaling quality of the equity price changes are therefore high. (Gunther et al., 2001)

The rating process is instead rather slow since deterioration or improvement of the conditions of a firm needs to be considered permanent through the cycle to result in a rating downgrade or upgrade. If it takes time for the rating agencies to make such a conclusion the rating changes will lag compared with the Merton model's calculated DD. Another possible cause of a lag is related to concerns about the rating agencies' independence of the issuers which are also their clients. This position of dependence might influence the timing of rating changes which would create a lag. Feinberg et al. (2004) test this by comparing rating changes between traditional rating agencies and independent rating agencies. Independence in this case means that the agencies are not receiving any fees from the issuing entities, that the entities have no possibility to preview their rating and that the agencies mainly base the rating on publicly available information. Feinberg et al. (2004) find that the independent agencies have a timelier and more accurate rating than the traditional agencies that tend to give a higher rating and respond to changes more slowly.

Different studies have been made to see if market data can be used to forecast rating changes and default. Kealhofer (2003) shows proof of that the KMV model can predict rating changes rather well and concludes that the KMV model, at that time, were better in predicting default than the actual credit ratings by the rating agencies. Hull et al. (2004) study the credit spread on credit default swaps to see if it can be used to anticipate rating changes by Moody's and they find that the credit spread have some forecasting ability. Gropp et al. (2006) test both the DD from the KMV model and the credit default swap spreads in their study where they investigate bank fragility in the EU. They find that market based measures have forecasting ability and that the distance to default exhibits lead times of 6-18 months. That the credit spread and the DD show similar results is not surprising since they are interlinked. The credit spread is settled on the market and as mentioned in the introduction it reflects the market's view on the credit risk of the company. The market based Merton model also incorporates the market's opinion when it measure credit risk. Considering the theory and the previous research the first hypothesis is made.

Hypothesis 1: The distance to default (DD) measure of the Merton model has a positive prediction ability of future rating changes.

The explanatory power of the market based indicators seems to be asymmetric. The price reaction is greater for downgrades than for upgrades. This asymmetry has been proven in different papers, for example Steadman (1990) or Halek and Eckles (2010). Both of these papers are event studies that study the stock market reaction of rating changes. The results are similar and Halek and Eckles confirm Steadman et al. results on the asymmetry between upgrades and downgrades. Upgrades do not result in a price reaction as downgrades do. A common way to explain the asymmetry on the market is that good news of a company is disclosed immediately and incorporated into the price. Bad news are not and a rating downgrade is therefore more of a negative surprise to the market. Or as Purda (2007) expresses it: "As a result, downgrades represent information not yet known by the market whereas upgrades confirm information that is already available."

This would indicate that a market based model as the Merton model has a better forecasting ability for rating upgrades since that information is incorporated in the market data. The information in the rating downgrades is not and seems to be revealed to the market by the rating agencies when a downgrade is made.

This theoretical view on the forecasting ability of the market based indicators given by the stock market's reaction is however not confirmed by empirical testing of market based models. On the contrary Hull et al. (2004) find evidence for that downgrades are significantly easier to predict than rating upgrades with their model that uses credit swap spreads. Crouhy et al. (2000) uses the KMV-model instead of spreads and find evidence for that it can anticipate downgrades but not upgrades of the credit rating up to a year in advance.

What kind of rating changes that actually are predictable and whether or not the market can indicate upgrades and downgrades in advance is ambiguous when looking at previous studies. This is an interesting aspect of the forecasting ability of the Merton model which leads to the second hypothesis.

Hypothesis 2: There is a difference in the Merton model's ability to predict upgrades and downgrades.

3. Methodology

This section will deal with what kind of methods we have used to find our data and to do our calculations and also how the regression analyses have been conducted. Simplifications and assumptions about the Merton model and the credit ratings by Moody's will also be presented here.

3.1 Sample

The companies in the sample are collected from the S&P 500 index. After excluding financial companies there are 419 companies left. To get a random selection of these companies the companies are sorted by their name (which is assumed to be given in a random order). Starting from the top of the sorted list all companies that had a rating from Moody's during the whole time period 2003-2009 were chosen to take part in the sample until a total number of 100 companies was reached. The limitation of 100 companies is made due to the time constraint of the research. All the financial data collected for the chosen companies were gathered from Thompson Reuters DataStream. A table with the list of all the firms in the sample, with their ticker and industry classification, is attached in appendix 2.

Using the collected data to calculate the individual firms' probability of default using the market based Merton model the model's usefulness in predicting actual credit rating changes can be estimated. The result from the Merton calculations will be evaluated in relation to the actual credit ratings by Moody's with regression analyses over time to see if there is a trend that indicates that the Merton model can predict future changes in the credit rating.

3.2 Moody's credit rating

Credit ratings by Moody's are used since they are easily retrievable on their web page in opposite of their competitors Standard & Poor's and Fitch. Another reason is that Moody's is the largest rating agency, in tight competition with Standard & Poor's. (Hill, 2002)

Monthly ratings for each firm are gathered. If there are different ratings for one firm during one month the last rating that specific month has been used. This is very uncommon in the sample. All ratings are long term ratings (1y<) and outlooks for possible rating changes have not been considered.

3.3 Translation

To be able to compare the ratings from Moody’s with the DD from the Merton model the credit ratings need to be translated into numbers. There are several ways to do this transformation but one method that is fairly common and fits the purpose and scope of this thesis well is to transform the ratings into an ordinal scale from 1 - 21 (see for example Bergman and Stäck (2009) and Nyberg and Zettergren (2006). Presented below is a table with the ordinal scale translator:

Table 1: Moody's rating - ordinary scale

Moody's	**Ord. scale**	**Moody's**	**Ord. scale**	**Moody's**	**Ord. scale**	**Moody's**	**Ord. scale**
Aaa	21	Baa1	14	B1	8	Ca	2
Aa1	20	Baa2	13	B2	7	C	1
Aa2	19	Baa3	12	B3	6		
Aa3	18	Ba1	11	Caa1	5		
A1	17	Ba2	10	Caa2	4		
A2	16	Ba3	9	Caa3	3		

In opposite of an ordinal scale a more extensive translation scale can be used. For example the EDF distribution can be used to capture more information. This is not necessary for the scope of this thesis but the EDF scale is presented in appendix 3 for interested readers.

3.4 Assumptions for calculations

To calculate the DD with the Merton model both market data and accounting data are needed. Also several assumptions and simplifications have to be made in order to use the model properly. The data needed for the calculations are the distress barrier, the market value of assets, the predicted asset growth and the volatility of the asset growth. Monthly data is used to perform as precise calculations as possible to be able to catch as many changes in ratings during the chosen time frame as possible. The data mining process and the simplifications made will be explained more in depth below.

3.4.1 The distress barrier

The distress barrier is calculated as the short term debt and current portion of long term debt plus half the amount of long term debt from the firm's balance sheet. This is supposed to represent the principal and interest payments (P&I) that are due within a year. Just as the original version of the Merton model this calculation is simplified by assuming that the company only has equity and zero coupon debt. Later and modified versions of the original Merton model has been able to incorporate some interest payments in the distress barrier but this could easily become very complicated. This simplification is reasonable to make according to Gray and Malone (2008).

The calculated distress barrier actually overstates the P&I to be paid within a year since it includes half the long term debt, this is an assumption that brings the model closer to reality. The empirical data from KMV finds that firms usually has gone default between short term and long term debt. Instead of just on short term debt as the original version of the Merton model implies. One explanation for this is that a firm may go into default due to liquidity problems as well. (Crouhy et al., 2000)

Since yearly balance sheets are used for the debt it is assumed to stay constant during all the months of each year. (Neither quarterly nor monthly balance sheets are available through DataStream.)

3.4.2 The market value of assets

The market value of the company's assets is assumed to be equal to the market value of equity plus the face value of total debt. The use of the face value of debt instead of the value of risky debt is a simplification that will be further explained in the simplification discussion. The market value of equity is easy retrievable since it is the market capitalization. That is; the amount of outstanding shares times the share price at the specific date. This data is retrieved for the whole time period (2003-2009) as daily data to be as specific as possible.

From the daily data, average market capitalization for each month is calculated. The monthly average market capitalization plus the face value of total debt from the company's balance sheet constitutes the value of total assets. Since the use of yearly balance sheets the face value of debt is assumed to be the same over all the months during each year as mentioned earlier in the method section.

3.4.3 The predicted asset growth

Asset growth is assumed to be equal to the risk free rate in the United States. 3-month US Treasury bill rate of returns has been retrieved for this purpose on a monthly basis. The use of the risk free rate as asset growth rate is consistent with the original Black and Scholes option pricing model that assumes risk neutral investors. That implies that investors require a return equal to the risk free rate. Thus the drift term $\mu = rf$ which facilitates the Black-Scholes equation. (Black and Scholes, 1973)

A complication of treating the drift term as the risk free rate of return is that it will slightly overstate the default probability since the actual growth usually is larger than the risk free rate. (Gray and Malone, 2008) This should not affect the results in this study very much since it is the relative change through time and not absolute levels that is of main interest.

3.4.4 The volatility in asset growth

The volatility in asset growth is assumed to be equal to the market capitalization divided by the market value of assets, this is multiplied with the volatility in equity value at each given time period. The volatility in the equity value is calculated as in Gropp et al. (2006) using daily stock price data for the whole period plus six month before, that is 2002-07-01. That implies the use of rolling six month averages in the price changes of the shares on the market and it is done in an effort to reduce noise. The volatility at each day during the period is calculated and transformed into monthly averages for the final Merton calculations.

3.5 Simplification discussion

Since the asset value and asset volatility are not directly observable they need to be estimated using the values that are observable; the equity value, the volatility of equity, face value of debt, risk free rate (and the contractual term). The two unknowns, asset value and asset volatility cannot be solved by simple algebra. It is however possible to solve the two unknowns by an iterative process. A software tool as "solver" in Microsoft Excel can be used to solve the two values. It is possible to solve asset value and asset volatility but it needs to be done for every observation which makes it a time consuming task.

By introducing two simplifications it is possible to estimate the asset value and volatility without doing any iteration. The first simplification is that the asset value is equal to the face value of debt plus the market value of equity. The second simplification is that the asset volatility is equal to the market value of equity divided by the asset value assumed by the first simplification multiplied by the volatility of equity. (Du and Suo, 2007)

But the simplifications have some drawbacks. If the probability of bankruptcy is high the face value of debt is much larger than the value of risky debt which will overstate the asset value and thereby understate the probability of default. The difference between the face value of debt and the value of risky debt does however not grow large enough to affect the probability of default significantly due to the characteristics of the companies in our sample. The companies in our sample are all large corporations that have a rating during the whole period which exclude companies that are delisted and being taken over, by other words, our sample do not contain any firms with a high probability of default.

The following examples shows the probability of default using both solver in excel and the simplifications that we have used for our further calculations. As expected the results are very close to each other even when the probability of default increases. ATI was one of the companies in the sample with the highest probability of default and both the methods gave very close results even in February 2009 when the DD went under 2. The comparison of the simplification and the solver is presented in table 2 below. The difference in the probability of default was roughly one percentage point (0,04264 - 0,03299). Therefore the simplifications made seem valid and can be used in order to save time without distorting the results.

Table 2: Solver versus simplification

Company	**Date**	**Method**	**D-t-D**	**Prob. of default**
ATI	jan 03	solver	4,043	2,64648E-05
ATI	jan 03	simple	4,124	1,8661E-05
ATI	jun 03	solver	3,335	0,00043
ATI	jun 03	simple	3,441	0,00029
ATI	feb 09	solver	1,721	0,04264
ATI	feb 09	simple	1,838	0,03299

3.6 Regression analyses

To investigate if the Merton model have any predictive power of the actual rating change by Moody's and if there is any difference in the predictability of downgrades or upgrades a panel data set is created. To be able to see the changes of the rating and the DD the first difference is calculated ((t+1)-t)) for both the rating and the DD. For the statistic analysis a logit-regression is used. A logit regression is chosen since the study aims to see the probability of a future event which makes a simple linear regression ill suited. (Brooks, 2008) With a logit regression model the dependent variable is transformed to a binary variable and the regression analysis tests the probability that the dependent variable is "1". In this case the probability of a rating change of some kind. Apart from a logistic regression a probit regression could be used for the same purpose. Probit regressions are performed with similar results why only logit regressions will be used through this thesis. This is an expected result since the difference between a logit and a probit regression usually is very small. (Brooks, 2008)

3.6.1 Dummy variables

To use a logit regression the rating changes has to be transformed into binary dummy variables. "1" represents a change in the rating and "0" represent no change. The drawback of the dummy variable transformation is that some information is lost. In this case rating changes above one step are reduced to one step. This should however not affect the analysis that much since there are few changes greater than one.

Table 3 below lists the different dummy variables used in the regression analyses. The change in DD is kept as a continuous variable (Δ(DD)).

Table 3: Dummy variables

Dummy variable	**Explanation**
dv_change_rating	1=upgrade or downgrade of the credit rating by Moody's 0=no change in the credit rating
dv_down rating	1=downgrade by Moody's 0=upgrade or no change in the credit rating
dv_up_rating	1=upgrade by Moody's 0=downgrade or no change in the credit rating by Moody's

3.6.2 Regressions in EViews 7

The statistical analysis is made with the econometric tool EViews. A spreadsheet containing information about the companies, their rating and DD calculated with the Merton model and the dummy variables is imported into EViews as a dated panel data set. To see if there is a lead lag relationship between the DD and the rating the generate function in EViews is used to construct lagged values on the ΔDD. By doing this Merton values at an earlier date is paired with more recent rating changes to find potential links between the Merton model's DD and the actual credit rating several months or years before an actual change in the credit rating by Moody's. When the values are lagged it is implied that the DD are been put earlier so that the actual ratings are lagged in contrast to the DD. The values are lagged with 1-12, 18 and 24 months.

The equation below for the logit regressions is taken from Brooks (2008).

$$F(z_i) = \frac{e^{z_i}}{1+e^{z_i}} = \frac{1}{1+e^{-z_i}} \tag{2}$$

The use of a logit regression model enables the values to be probabilities between 0 and 1. Where F is the cumulative logistic distribution and z is the vector of independent variables. Estimated the logit regression is the following:

$$P_i = \frac{1}{1+e^{-(B_0+B_1X_1+B_2X_2\ldots)}} \tag{3}$$

P_i = the probability that $y_i = 1$

e = a constant, approximately 2,718

B = coefficient of X

X = independent variable

In EViews the “Estimate equation”-tool is used to perform the logit-regressions. Three regressions for are performed. One of the three regressions are a test of rating changes in general, both upgrade and downgrade. The two other regressions are made on downgrades and upgrades separately. The independent variables are the non lagged Δ(DD) and all the lags of the Δ(DD) in order to test them together and to identify differences between different time periods of lag to find significant correlations to the dependent variable.

All the independent variables are calculated in the same sample since this gives a better regression than by calculating them one by one. The same equation is repeated for upgrades and downgrades separately as well. The drawback of gathering all the values in one sample is that several observations are lost since EViews evens the different series of data out to exactly match each other. This reduces the number of observations in the logit regressions from 8400 observed values to 5900. This is unavoidable and does not affect the results negatively.

What is implied when running regressions with the downgrades and upgrades separately is that a downgrade event is not assumed to have an effect on an upgrade. This assumption is fairly acceptable and has to be made in order to run these kinds of regressions. To deal with this matter interaction variables regressions are introduced and described later in this chapter.

3.6.3 Robustness of the logit regressions

To test the model's robustness the same type of regressions as above are made with quarterly data. The model is robust if the results from the quarterly data are similar to the results from the monthly data. The values are lagged eight times, that is eight quarters, to get a maximum lag of two years, just as for the monthly lagged regressions. Due to the fact that the sample is reduced to only quarterly data the number of observations is reduced for these regressions.

3.6.4 Interpretation of logit regressions

Because of the use of logit-regressions the coefficients from EViews has to be interpreted after they have been adjusted with equation 4 due to the fact that the dependent variable in the data set is binary and only consists of either the value "0" or "1". (Brooks, 2008)

In the results presented later the adjustment formula does not change the coefficients radically since one part of the formula is the mean value from all the observations in the sample and the mean value from this data set is very low. Below the adjustment formula is presented:

$$k * F(\bar{z}) = k * \frac{1}{1 + exp(\bar{z})} = marginal\ effect \tag{4}$$

Where

c = constant

k = coefficient

$\bar{z} = c + (k * \bar{k})$

Coefficients from the logit regressions are interpreted as the percentage increased or decreased likelihood that the dependent dummy variable is "1" when there is an increase of one step in the independent variable (an increase with one standard deviation in the DD). That is the increased or decreased likelihood for a rating change of some kind, dependent on what kind of regressions that has been made. For example if the coefficient for a logit regression is 0,25 when the dependent variable is the dummy variable for a downgrade ("1" is a downgrade) the likelihood that a downgrade happens is increased with 25% when the DD increases with one standard deviation. The interpretation of the coefficients will be explained in connection to each specific result that is presented later in the thesis.

3.6.5 Interaction variables regressions

The regressions above are simple logit regressions and the regressions are conducted on the whole sample of rating changes as well as downgrades and upgrades separately. In order to find further evidence for a difference in the predictability of downgrades versus upgrades, interaction variables are used. Interaction variables allow testing of the predictability difference between upgrades and downgrades at the same time in the same sample instead of isolated from each other. Interaction variables regressions are made both on the quarterly data and the monthly data.

As with the simple logit regressions all lags were included in the same regression but because of correlation between the independent variables, since they were transformed as interaction variables, they were also run one by one to avoid this issue that distorts the results.

Interaction variables consisting of the dummy variable for a rating upgrade times the Δ(DD) as well as the dummy variable for a rating downgrade times the Δ(DD) were constructed. This is made in order to do to two different kinds of interaction variables regressions, this matter is explained more in detail in connection with the results. Due to the fact that the dummy variable for rating upgrades perfectly predicts the dummy variable for rating changes the dummy variable alone cannot be run as an independent variable. This modification is unavoidable to be able to conduct the regressions in EViews.

3.6.6 Interpretation of interaction variables

The interaction variables are interpreted as the effect on the dependent variable in the event of an upgrade or a downgrade. The standalone variable is then interpreted as the effect on the dependent variable when there is not an upgrade or a downgrade. For all the observations where the dummy variable is zero, the whole expression will be just the Δ(DD).

3.6.7 Statistical significance

Statistical significance for the regressions is tested at the 10%, 5% and 1% level and is found in the regression tables as the p-value. Results without statistical significance can still be of some value since the coefficients for several observations can indicate a certain trend. But without statistical significance it is impossible to conclude a certain result with scientific correctness. This thesis aims to present results with statistical significance but from results that lack significance some conclusions will be tried to be drawn upon coefficients themselves.

3.6.8 Alternative regressions

For the regressions presented in this section so far the Δ(DD) and a dummy variable for the rating change are used. In order to test for stronger significance the same tests were performed with dummy variables for both the change in DD and the rating change. The same simple logit regressions as earlier was performed but with dummies as both dependent and independent variable. Also a regression analysis with the rolling one year average standard deviation of the Δ(DD) against the dummy variable for rating change was constructed in order to test if high volatility in the DD could have any correlation to a rating change. This is also done in order to investigate if an increased volatility could be an explanation of the different signs of the coefficients from the logit regressions that will be presented in the result section. The thought behind this is that the DD starts to fluctuate more before a rating change.

3.7 Method critism

One source of error for the results in this thesis can be traced to the chosen sample of firms. With only very stable firms in the sample with very few rating changes the results can be hard to generalize for a larger population. It can also be hard to reach sensible regression results since the correlation might be weak due to the low amount of rating changes.

Another source of error could be the way that the credit ratings are translated into numbers. The use of an ordinal scale excludes some facts and do not give the same information in the translation as an EDF-scale would do for example.

Finally the use of logit regressions which implies the use of a binary dependent variable may cause some distortion since some information is lost. The use of other kind of regressions would not be suitable for the data set in this thesis but this is still a fact that the reader has to be aware of.

4. Results and analysis

In this section the results of the data mining and the regression analyses will be presented as well as calculations and comparisons between credit ratings and our findings. Also the analysis of the results will be presented here.

4.1 Descriptive statistics

When testing the monthly data the total sample consists of 8400 observations. These are reduced to 5900 observations when using several lagged independent variables in the same regression. For the total sample the dependent variable, the dummy variable, is equal to "1" only 144 times. That implies a "0" for the rest and therefore the total amount of rating changes is very low. The amount of rating changes is further reduced to only 117 observations when performing regression analyses due to the fact that the total number of observations is reduced.

The rating changes are distributed in 70 upgrades and 74 downgrades. A large majority of the changes were one step changes but 19 changes were changes of more than one step and only 4 were changes of more than 2 steps. Due to the decreased number of observations the regression analyses uses 56 downgrades and 61 upgrades.

When using quarterly data the number of observations is reduced to 2100, that is one fourth of the total sample. Just like the full sample the number of observations is reduced when performing regression analyses; in this case to 1900 observations. The number of rating changes falls to 135 which mean that there are relatively more rating changes compared to the total number of observations in the quarterly data than the monthly data. Also this number is reduced when performing regression analyses, in this case to 108 rating changes. The 108 rating changes are distributed as 58 upgrades and 50 downgrades.

To ensure that the independent variables do not vary in a way that they might distort the results maximum and minimum values are calculated. There is a fairly large max-min spread but divided over the individual firms in the sample the independent variables are not varying too much to be able to use them. None of the observations had to be excluded. The following table concludes the statistics for the independent variables, the DD by the Merton model.

Table 4.

	Quarterly data	**Monthly data**
Mean	12,05529	12,05529
median	11,36946	11,39612
Max	52,60117	56,33203
Min	1,512895	1,420086
max-min	51,08828	54,91194
std. dev.	5,634605	5,720358

4.2 Interpretation of the regression analyses

The results from the regression analyses are used to see if there are any correlations between the DD and the credit rating for different lags. The intuition is that an increased DD should cause a higher credit rating since a lower probability of default should result in a better credit rating. In the same way, a decrease in DD should result in a lower credit rating.

When the coefficients in the results are described and explained it is implied that they have been adjusted in accordance with the adjustment formula mentioned in the method section. Therefore the coefficients from the result tables will differ slightly from the coefficients explained in plain text in connection to the result tables. The coefficients that will be dealt with and explained in the result section are coefficients with statistical significance. Coefficients that lack both statistical significance and other explanatory values will not be described any further.

Several of the regressions described in the method section showed very low significance or irrelevant results and will just be mentioned and described quickly. Focus will be aimed at results from the regression analyses that can bring any clearance or foundation to accept or dismiss the hypotheses and to be able to build an adequate analysis upon.

In the regression tables presented in the result section and the appendix the following system is used to indicate statistical significance:

Table 5.

	Significance level
*	10%
**	5%
***	1%

4.3 Results

4.3.1 Predict a future rating change

The monthly logit regression for overall rating change shows some, though very weak, statistical significance at the 10% level. An increase of one unit in DD increases the likelihood that the dependent variable should be ”1” 12 months ahead. Differently put, an increase with one standard deviation in the DD increases the likelihood for a rating change in one year with 15,24% (see table 6 below).

Table 6: Regression table – rating change monthly

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-3.893095	0.096268	-40.44002	0.0000
No lag	-0.021583	0.052807	-0.408709	0.6828
1 month lag	-0.048616	0.056978	-0.853256	0.3935
2 month lag	-0.027205	0.056946	-0.477739	0.6328
3 month lag	-0.017418	0.056501	-0.308273	0.7579
4 month lag	-0.045205	0.064335	-0.702659	0.4823
5 month lag	-0.021599	0.094042	-0.229675	0.8183
6 month lag	0.070124	0.094596	0.741302	0.4585
7 month lag	-0.002979	0.093204	-0.031960	0.9745
8 month lag	0.060569	0.089596	0.676025	0.4990
9 month lag	-0.029752	0.091237	-0.326099	0.7443
10 month lag	0.095598	0.087231	1.095915	0.2731
11 month lag	-0.056832	0.087056	-0.652821	0.5139
12 month lag	0.155527	0.088581	1.755757	0.0791*
18 month lag	0.083498	0.089664	0.931237	0.3517
24 month lag	-0.020749	0.086254	-0.240552	0.8099

Dep. variable:	DV_CHANGE_RATING
McFadden R-squared	0.007055
Log likelihood	-570.4815
Avg. log likelihood	-0.096692
Total obs	5900
Obs with Dep=0	5783
Obs with Dep=1	117

The regression analysis based on the quarterly data with the same dependent variable shows no statistical significance for any of the lagged periods. Neither can the coefficients explain any trend due to the fact that they change from negative to positive in a random order. The regression analysis for the quarterly data is therefore only presented in appendix 4 for the interested reader and will not be considered any further in this thesis.

4.3.2 Predict a future rating downgrade separately

The regression for only downgrades is conducted in a similar way as the last example but the dependent variable is a dummy variable that only considers downgrades by Moody's. In the regression for monthly data there are two lags that show statistical significance.

12 months ahead of a rating downgrade there is some significance at the 10% level which means that an increase with one standard deviation in the DD increases the likelihood of a "1" as dummy variable. That is an increased likelihood with 22,14% of a rating downgrade one year later. In 18 months ahead of an actual rating change the regression indicates that there is a result with statistical significance at the 5% level. The interpretation is that an increase in the DD by one standard deviation explains a 25,57% increased likelihood for a future rating downgrade one and a half year later. The coefficients of these lags are positive which is rather strange and not intuitive considering the assumed relationship between the DD and the rating. See table 7 below.

Table 7: Regression table – downgrades monthly.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-4.678010	0.142113	-32.91748	0.0000
No lag	-0.071530	0.069768	-1.025257	0.3052
1 month lag	-0.038213	0.075688	-0.504871	0.6136
2 month lag	-0.068524	0.073583	-0.931249	0.3517
3 month lag	-0.035948	0.079428	-0.452585	0.6508
4 month lag	-0.054560	0.088717	-0.614992	0.5386
5 month lag	0.031759	0.140857	0.225469	0.8216
6 month lag	0.188066	0.131033	1.435251	0.1512
7 month lag	0.028880	0.131062	0.220350	0.8256
8 month lag	0.095282	0.124752	0.763774	0.4450
9 month lag	0.032039	0.127319	0.251643	0.8013
10 month lag	0.131847	0.118691	1.110837	0.2666
11 month lag	0.058382	0.118817	0.491362	0.6232
12 month lag	0.223470	0.117718	1.898352	0.0576*
18 month lag	0.258134	0.129700	1.990240	0.0466**
24 month lag	0.094974	0.128183	0.740929	0.4587

Dep. variable:	DV_DOWN_RATING
McFadden R-squared	0.029031
Log likelihood	-307.3558
Avg. log likelihood	-0.052094
Total obs	5900
Obs with Dep=0	5844
Obs with Dep=1	56

To test the robustness of the regression above average quarterly data is used (see table 8 below). The regression indicates that a future downgrade can be predicted one quarter ahead as well as four quarters, one year, ahead with significance on the 5% level.

Table 8: Regression table – downgrades quarterly

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-3.601315	0.156280	-23.04404	0.0000
No lag	-0.028723	0.061225	-0.469142	0.6390
1 quarter lag	-0.156661	0.075339	-2.079428	0.0376**
2 quarter lag	0.094723	0.077717	1.218809	0.2229
3 quarter lag	0.016560	0.081660	0.202795	0.8393
4 quarter lag	0.153423	0.076993	1.992699	0.0463**
5 quarter lag	0.027279	0.075626	0.360705	0.7183
6 quarter lag	0.088035	0.080471	1.093997	0.2740
7 quarter lag	-0.032172	0.078649	-0.409058	0.6825
8 quarter lag	0.090575	0.077688	1.165881	0.2437

Dep. variable:	DV_CHANGEDOWN

McFadden R-squared	0.028587
Log likelihood	-224.6059
Avg. log likelihood	-0.118214

Total obs	1900
Obs with Dep=0	1850
Obs with Dep=1	50

The coefficient -0,156661 for the one quarter lagged variable is interpreted as a decreased likelihood with 15,26% of an actual rating downgrade one quarter later. The coefficient 0,153423 for the four quarters lagged variable indicates that the probability for a rating downgrade increases with 14,93% in one year. This is statistically significant at the 5% level.

The significant coefficients in the quarterly date have both a negative sign and a positive sign which cause the same questions as for the monthly coefficients.

4.3.3 Predict a future rating upgrade separately

The same procedure as for the previous regressions is conducted in order to analyze the possibility to predict rating upgrades but the dummy variable is changed to only consider upgrades. Neither the regression analysis for the monthly lagged values nor the quarterly lagged values shows any statistical significance. They do not give any explanatory value of importance either since there is no trend that can be analyzed. The regression tables for the upgrades separately are therefore only presented in appendix 5 and 6 for the interested reader.

4.3.4 Interaction variables regression analyses

The use of interaction variables allow the testing of upgrades and downgrades in the same sample. Regressions are made with all the lags in one sample as well as separately in an attempt to avoid multicollinarity between the independent variables. The results from the separate regressions are however not any better than the aggregated regressions.

The interaction variable regressions shows high statistical significance for several different values and the regressions are repeated with several differences to try to find out an intuitive result. But the attempts to reach intuitive explanations to the coefficients are insufficient. The sign of the coefficients makes no sense and might be distorted by multicollinarity between the independent variables that seem to depend on each other and shift in a confusing pattern. A multicollinarity test is made that shows some proof of multicollinarity.

So even with statistical significance for several lags it is impossible to fully interpret the results from the interaction variables regressions. Because of the inconclusive results from the interaction variables regressions they will not be consider any further in this thesis. The regression tables for the interaction variables based on monthly data are presented in appendix 7 and 8 for the interested reader. The interaction variables regressions based on quarterly data are presented in appendix 9 and 10. Two kinds of interaction variables regressions are presented; one with the interaction variable for downgrades and one with the interaction variable for upgrades.

Intuitively these should show exactly the same results. But since the fact that the dummy variable used only considers either rating upgrades or rating downgrades all the observations that are only stable ratings will distort the results to some extent and obstruct the two different kinds of regression analyses to show identical results.

4.3.5 Alternative regressions results

When testing logit regressions for dummy variables both as independent and dependent variable the results are inconclusive due to the lack of variation in the different series.

The regression made of the rolling one year average standard deviation of the Δ(DD) versus the dummy variable for rating changes was also inconclusive.

These alternative regressions will not be further considered due to lack of statistical significance and uninterpretable results and will not be presented in this section or in the appendix.

4.4 Results summary

Due to the lack of significance and reliability in the coefficients from the regressions and inconclusive results from alternative regressions, as well as interaction variables regressions, the simple logit regressions alone will constitute the foundation for this summary and for the further analysis and discussion.

When filtering the logit-regressions and conducting separate logit-regressions for upgrades and downgrades some statistical significance for the Merton model's ability to predict downgrades is proven. Besides this, there is no evidence of statistical significance in the other regression analyses. Neither can the coefficients from the regressions analyses, even without statistical significance, be used since they are inconclusive. There is no visible trend that can explain the hypotheses of this thesis either. With other words, the results that are of importance are the few lagged values with statistical significance from the downgrade logit regressions.

4.5 Analysis of the results

The analysis is initiated by discussing the overall regressions made with both upgrades and downgrades between the Merton model's DD and the rating changes. The monthly regression shows a weak significance one year in advance. This is however not supported by the result of the quarterly regression that showed none significance nor trend in the data. That means that the robustness of the regression analysis for a rating change (either up or down) is low and hard to draw conclusions upon.

The separation of the downgrades and upgrades gives a more interesting result. Regressions for the upgrades show no significance in the monthly or the quarterly data. But what is interesting is that this differs from the results of the rating downgrades. The monthly and the quarterly data from the downgrades regressions have significant lags one quarter and around one year before a rating change.

A disturbing fact regarding the coefficients in the downgrade regressions is that they have different signs; lag one in the quarterly data has a negative sign and the others have positive signs. The negative coefficient for lag one in the quarterly data seems more intuitive than the coefficients for the other significant results. A negative coefficient means that an increase in DD (decrease in credit risk) with one standard deviation decreases the likelihood of a future downgrade. A positive coefficient means that an increase in DD increases the probability for a rating downgrade which is simply not logic. The positive coefficients are shown to be robust since they show significance both in the monthly and quarterly data one year in advance. But the interpretation of the coefficients is still troubling.

Another inconsistency in the result is that the quarterly downgrade data show statistical significance for both one quarter and one year in advance but the monthly data show significance one year in advance as well as one and a half year in advance. The significance is also higher when using quarterly data but our monthly data are more precise. Even though the results are inconsistent and confusing some conclusions can be made. There is prediction ability several months ahead of a rating downgrade but the exact time period in advanced is uncertain.

The non-intuitive interpretation of the positive coefficients for several of the statistical significant results is confusing and hard to explain. A possible explanation might be that an increased volatility in the DD a certain time period before an actual credit rating makes the coefficient to be of the opposite value (negative/positive) than supposed. To test this an alternative regression method with the volatility in DD instead of the actual difference in DD is used as the independent variable but no significance or other interesting results is found. But even though the results do not show any significance we find the explanation that high volatility ahead of a rating change is plausible.

Since the regressions only considering upgrades show no significance we can conclude that it is not possible to forecast rating upgrades with the methods and the data set that we have used. Due to the fact that we actually are able to predict future downgrades we can accept both our first and second hypothesis. It is possible to predict some future rating changes and there is a difference in the predictability of upgrades and downgrades. It should be emphasized that our findings are to some extent inconclusive and with weak statistical significance so more research is needed in this area. On the other hand our findings do give some support to earlier research that has found downgrades to be more easily predictable than upgrades and our research confirms their research to some extent. What is disappointing is that our findings can hardly contribute anything to practitioners.

The absence of significance in several of the regressions can be explained by the use of the chosen data set. With a sample consisting of just S&P500-firms there are not many rating changes. The stickiness of credit ratings are very visible in the chosen sample and with the low percentage of rating changes among the total number of observations the fact that it is hard to find significant correlations between the DD and the rating changes is not surprising. For several firms in the sample there are no rating change at all during the total time frame and with a DD that jumps up and down it is obvious that the regression analyses are obstructed to some extent.

What is also disappointing is the inability of the interaction variables regressions to give intuitive results. These kinds of regressions are considered the most correct for the purpose since they have less simplistic assumptions. When looking in the rear-view mirror our data set is far from perfect to perform these kinds of regressions upon. But we can also conclude that it should have been hard to perfectly estimate the DD with the Merton model and to retrieve actual credit ratings for a sample this large if not using the kind of firms that we actually did.

5. Conclusions and future research

This section will conclude the thesis and present some overall comments about the implications of the results. Also suggestions for future research will be provided.

5.1 Conclusions

To reconnect to our initial purpose it is hard to draw any significant conclusions but we can support the criticism of slow credit ratings since a market based model can forecast rating changes to some extent. That implies that the market based Merton model quicker adjusts to changed conditions for companies than the credit rating from the agencies do. But how great this lag is we cannot say with any sufficient reliability.

The proven asymmetry in the predictability of upgrades versus downgrades is very hard to generalize upon since it is ambiguous and vague. Downgrades according to this thesis are predictable to some extent and this indicates that the market is better to incorporate information that leads to downgrades in the stock prices. But this is not the case looking at previous event studies on stock reaction to rating changes that shows a negative reaction after a rating downgrade. This implies that a lot of responsibility is placed upon the rating agencies and that investors do trust the rating agencies. It appears that investors do not fully use credit risk models on their own. An explanation to that might be that the investors feel that the credit risk models are not able to replace the rating given by the rating agencies.

Lagging credit ratings on the credit market creates several potential dangers for the financial markets. If firms are not properly graded by the rating institutions, whether they are overrated or underrated, it could imply that they receive maladjusted loan terms and decreased financial flexibility. This could of course have major negative impact on both the financial markets but also for the society at large.

Investors could also be misinformed so that they may misjudge investment opportunities in firms that are rated as safe but do not live up to that standard. Worst case scenario is something in the line with the Enron scandal or the Lehman Brothers collapse, which heavily influenced both the financial markets and the general public negatively since the credit rating heavily understated the real credit risk.

The use of the Merton model to calculate credit risk could be used as a supplementary measure to ensure that the credit rating or credit terms of a specific firm is as accurate as it possibly could be.

5.2 Future research

Several questions can be raised from the findings in this study. What could be interesting to further investigate is why it is possible to forecast future downgrades but not upgrades. What are the reasons for this and what consequences may it imply?

A major problem with our study has been that our sample contains very few rating changes and it makes it hard to find statistical significance that the Merton model can predict future rating changes. Therefore it should be interesting to use our study as a base but switch the sample to firms that have more volatile credit ratings. With a different data set future studies could hopefully confirm our findings but with higher significance and better precision.

The relation between actual credit ratings and the Merton model obviously exists; therefore future research could study how close this relation is. How much of the credit rating is based on quantitative credit risk model calculations and how much is based on the discretion of Moody's analysts? This could also be further developed into a discussion of the rating agencies independence and slow rating process.

Anyway, there are several reasons to further investigate the intriguing credit market and credit ratings and hopefully our study and future research can optimize the way that the credit market works.

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Appendix

Appendix 1

The Black-Scholes option pricing formula

c = $S_0 N(d_1) - Xe^{-rt}N(d_2)$

p = $Xe^{-rt}N(-d_2) - S_0 N(-d_1)$

$d_1 = \frac{\ln\left(\frac{S_0 N}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$

$d_2 = d_1 - \sigma\sqrt{t}$

<u>Interpretation of the Black-Scholes equations</u>

c = price of a call option

p = price of a put option

S_0 = present value of the underlying asset

N = normal distribution

X = strike price

e = a constant, approximately 2,718

r = risk free rate

t = time to expiration

σ = volatility

Appendix 2

Ticker symbol	Company	Industry
AA	Alcoa Inc	Materials
ABC	AmerisourceBergen Corp	Health Care
ABT	Abbott Laboratories	Health Care
ADM	Archer-Daniels-Midland Co	Consumer Staples
ADP	Automatic Data Processing	Information Technology
AEE	Ameren Corp	Utilities
AEP	American Electric Power	Utilities
AES	AES Corp	Utilities
AET	Aetna Inc	Health Care
AGN	Allergan Inc	Health Care
AMAT	Applied Materials Inc	Information Technology
AMD	Advanced Micro Devices	Information Technology
AMT	American Tower Corp A	Telecommunications Services
AN	AutoNation Inc	Consumer Discretionary
APA	Apache Corporation	Energy
APD	Air Products & Chemicals Inc	Materials
ATI	Allegheny Technologies Inc	Materials
AVP	Avon Products	Consumer Staples
AVY	Avery Dennison Corp	Industrials
AZO	AutoZone Inc	Consumer Discretionary
BA	Boeing Company	Industrials
BAX	Baxter International Inc.	Health Care
BBY	Best Buy Co. Inc.	Consumer Discretionary
BCR	Bard (C.R.) Inc.	Health Care
BDX	Becton Dickinson	Health Care
BHI	Baker Hughes Inc	Energy
BLL	Ball Corp	Materials
BMS	Bemis Company	Materials
BWA	BorgWarner	Consumer Discretionary
CA	CA, Inc.	Information Technology
CAG	ConAgra Foods Inc.	Consumer Staples
CAH	Cardinal Health Inc.	Health Care
CAM	Cameron International Corp.	Energy
CAT	Caterpillar Inc.	Industrials
CBS	CBS Corp.	Consumer Discretionary

CCL	Carnival Corp.	Consumer Discretionary
CEG	Constellation Energy Group	Utilities
CHK	Chesapeake Energy	Energy
CI	CIGNA Corp.	Health Care
CLX	Clorox Co.	Consumer Staples
CMI	Cummins Inc.	Industrials
CMS	CMS Energy	Utilities
CNP	CenterPoint Energy	Utilities
COP	ConocoPhillips	Energy
COST	Costco Co.	Consumer Staples
CPB	Campbell Soup	Consumer Staples
CSC	Computer Sciences Corp.	Information Technology
CTL	CenturyTel Inc	Telecommunications Services
CVS	CVS Caremark Corp.	Consumer Staples
CVX	Chevron Corp.	Energy
D	Dominion Resources	Utilities
DD	Du Pont (E.I.)	Materials
DE	Deere & Co.	Industrials
DELL	Dell Inc.	Information Technology
DF	Dean Foods	Consumer Staples
DHR	Danaher Corp.	Industrials
DNR	Denbury Resources Inc.	Energy
DO	Diamond Offshore Drilling	Energy
DOV	Dover Corp.	Industrials
DOW	Dow Chemical	Materials
DRI	Darden Restaurants	Consumer Discretionary
DTE	DTE Energy Co.	Utilities
DVA	DaVita Inc.	Health Care
DVN	Devon Energy Corp.	Energy
ECL	Ecolab Inc.	Materials
ED	Consolidated Edison	Utilities
EL	Estee Lauder Cos.	Consumer Staples
EMN	Eastman Chemical	Materials
EMR	Emerson Electric	Industrials
EOG	EOG Resources	Energy
EP	El Paso Corp.	Energy
EQT	EQT Corporation	Utilities
ETN	Eaton Corp.	Industrials
EXC	Exelon Corp.	Utilities

FDX	FedEx Corporation	Industrials
FE	FirstEnergy Corp	Utilities
FLS	Flowserve Corporation	Industrials
GD	General Dynamics	Industrials
GE	General Electric	Industrials
GIS	General Mills	Consumer Staples
GLW	Corning Inc.	Industrials
GR	Goodrich Corporation	Industrials
HAL	Halliburton Co.	Energy
HAS	Hasbro Inc.	Consumer Discretionary
HD	Home Depot	Consumer Discretionary
HES	Hess Corporation	Energy
HON	Honeywell Int'l Inc.	Industrials
HPQ	Hewlett-Packard	Information Technology
HRL	Hormel Foods Corp.	Consumer Staples
HRS	Harris Corporation	Information Technology
HUM	Humana Inc.	Health Care
IBM	International Bus. Machines	Information Technology
IFF	International Flav/Frag	Materials
IGT	International Game Technology	Consumer Discretionary
IR	Ingersoll-Rand PLC	Industrials
KO	Coca Cola Co.	Consumer Staples
MO	Altria Group Inc	Consumer Staples
STZ	Constellation Brands	Consumer Staples
TEG	Integrys Energy Group Inc.	Utilities
XOM	Exxon Mobil Corp.	Energy

Sector summary

Consumer discretionary	10
Consumer staples	14
Energy	14
Health care	11
Industrials	17
Information technology	9
Materials	10
Telecommunications Services	2
Utilities	13
	100

Appendix 3

The EDF distribution

Problematic with this distribution is that it may change from year to year. Below the EDF translator of Moody's credit ratings by Purda, D.Lynnette (2007) is presented:

Rating	EDF
Aaa	0,02
Aa1	0,03
Aa2	0,03
Aa3	0,06
A1	0,08
A2	0,13
A3	0,14
Baa1	0,22
Baa2	0,26
Baa3	0,39
Ba1	0,50
Ba2	0,79
Ba3	1,29
B1	1,97
B2	3,49
B3	5,38
Caa1	12,44
Caa2	20,00
Caa3	20,00
Ca	20,00
C	20,00

Appendix 4

Presented below is the regression analysis table for the logit regression considering rating changes, either up or down, based on quarterly data:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-2.800819	0.107152	-26.13882	0.0000
No lag	0.170923	0.276644	0.617843	0.5367
1 quarter lag	-0.064650	0.050688	-1.275448	0.2022
2 quarter lag	0.004933	0.053683	0.091895	0.9268
3 quarter lag	0.013608	0.055787	0.243935	0.8073
4 quarter lag	0.037300	0.052888	0.705253	0.4807
5 quarter lag	0.006264	0.053017	0.118156	0.9059
6 quarter lag	0.018596	0.054385	0.341932	0.7324
7 quarter lag	-0.028720	0.052831	-0.543616	0.5867
8 quarter lag	0.031302	0.050991	0.613877	0.5393

Dep. variable:	DV_CHANGERATING

McFadden R-squared	0.005005
Log likelihood	-412.4834
Avg. log likelihood	-0.217097

Total obs	1900
Obs with Dep=0	1792
Obs with Dep=1	108

Appendix 5

Presented below is the regression analysis table for the logit regression considering upgrades based on monthly data:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-4.633129	0.141381	-32.77051	0.0000
No lag	0.025428	0.073321	0.346808	0.7287
1 month lag	-0.076995	0.081771	-0.941591	0.3464
2 month lag	0.022480	0.080002	0.280996	0.7787
3 month lag	-0.047906	0.082346	-0.581765	0.5607
4 month lag	0.027157	0.104253	0.260493	0.7945
5 month lag	-0.085898	0.122630	-0.700469	0.4836
6 month lag	-0.056274	0.126033	-0.446506	0.6552
7 month lag	-0.028514	0.126356	-0.225667	0.8215
8 month lag	0.022034	0.120706	0.182539	0.8552
9 month lag	-0.096634	0.121225	-0.797147	0.4254
10 month lag	0.073710	0.120089	0.613793	0.5394
11 month lag	-0.173876	0.117677	-1.477569	0.1395
12 month lag	0.046255	0.128934	0.358747	0.7198
18 month lag	-0.075665	0.117032	-0.646531	0.5179
24 month lag	-0.100945	0.111660	-0.904040	0.3660

Dep. variable:	DV_UP_RATING
McFadden R-squared	0.008505
Log likelihood	-336.6773
Avg. log likelihood	-0.057064
Total obs	5900
Obs with Dep=0	5839
Obs with Dep=1	61

Appendix 6

Presented below is the regression analysis table for the logit regression considering upgrades based on quarterly data:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-3.533414	0.153387	-23.03597	0.0000
No lag	-0.056431	0.063264	-0.891997	0.3724
1 quarter lag	0.028963	0.064029	0.452346	0.6510
2 quarter lag	-0.085276	0.070114	-1.216247	0.2239
3 quarter lag	0.022075	0.073620	0.299856	0.7643
4 quarter lag	-0.071962	0.069820	-1.030673	0.3027
5 quarter lag	0.004964	0.072393	0.068574	0.9453
6 quarter lag	-0.041003	0.071111	-0.576602	0.5642
7 quarter lag	-0.029640	0.069207	-0.428281	0.6684
8 quarter lag	-0.021082	0.065100	-0.323842	0.7461

Dep. variable: DV_CHANGEUP

McFadden R-squared	0.006053
Log likelihood	-257.9067
Avg. log likelihood	-0.135740

Total obs	1900
Obs with Dep=0	1842
Obs with Dep=1	58

Appendix 7

Presented below is the interaction variable regression analysis table, based on an interaction variable considering downgrades, on a monthly basis:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-4.058921	0.105030	-38.64552	0.0000
No lag	0.008320	0.058808	0.141472	0.8875
1 month lag	-0.058223	0.064312	-0.905316	0.3653
2 month lag	0.002274	0.063309	0.035914	0.9714
3 month lag	-0.031942	0.065597	-0.486937	0.6263
4 month lag	0.039152	0.082415	0.475063	0.6347
5 month lag	-0.051481	0.098024	-0.525187	0.5995
6 month lag	-0.019166	0.101207	-0.189378	0.8498
7 month lag	-0.023165	0.099649	-0.232469	0.8162
8 month lag	0.017773	0.097502	0.182282	0.8554
9 month lag	-0.059943	0.099055	-0.605150	0.5451
10 month lag	0.071259	0.097146	0.733519	0.4632
11 month lag	-0.080781	0.096745	-0.834985	0.4037
12 month lag	0.090071	0.100712	0.894349	0.3711
18 month lag	0.023275	0.096057	0.242302	0.8085
24 month lag	-0.028307	0.091367	-0.309812	0.7567
IAV(DV*no lag)	0.176921	0.404474	0.437409	0.6618
IAV(DV*lag1)	-0.793654	0.292610	-2.712327	0.0067***
IAV(DV*lag2)	-0.550131	0.264507	-2.079831	0.0375**
IAV(DV*lag3)	-1.077276	0.289181	-3.725270	0.0002***
IAV(DV*lag4)	-1.569266	0.390658	-4.016978	0.0001***
IAV(DV*lag5)	1.505138	0.704049	2.137830	0.0325**
IAV(DV*lag6)	2.433170	0.715992	3.398321	0.0007***
IAV(DV*lag7)	0.187269	0.476552	0.392966	0.6943
IAV(DV*lag8)	0.899366	0.567519	1.584732	0.1130
IAV(DV*lag9)	1.627893	0.756866	2.150834	0.0315**
IAV(DV*lag10)	-0.034219	0.667634	-0.051254	0.9591
IAV(DV*lag11)	-1.508393	0.745912	-2.022214	0.0432**
IAV(DV*lag12)	3.383650	0.780508	4.335191	0.0000***
IAV(DV*lag18)	0.753259	0.889735	0.846610	0.3972
IAV(DV*lag24)	-0.149689	1.004790	-0.148976	0.8816

IAV = interaction varible,
DV = dummy variable

Dep. variable:	DV_CHANGE_RATING
McFadden R-squared	0.097934
Log likelihood	-518.2683
Avg. log likelihood	-0.087842
Total obs	5900
Obs with Dep=0	5783
Obs with Dep=1	117

Appendix 8

Presented below is the interaction variable regression analysis table, based on an interaction variable considering upgrades, on a monthly basis:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-4.199377	0.111734	-37.58363	0.0000
No lag	-0.056673	0.059362	-0.954701	0.3397
1 month lag	-0.034616	0.063124	-0.548389	0.5834
2 month lag	-0.053979	0.062221	-0.867533	0.3856
3 month lag	-0.019125	0.065446	-0.292231	0.7701
4 month lag	-0.023744	0.073628	-0.322481	0.7471
5 month lag	0.025924	0.111310	0.232898	0.8158
6 month lag	0.142076	0.108697	1.307080	0.1912
7 month lag	0.009876	0.107161	0.092161	0.9266
8 month lag	0.065247	0.104292	0.625618	0.5316
9 month lag	0.023051	0.105982	0.217502	0.8278
10 month lag	0.108680	0.100474	1.081682	0.2794
11 month lag	0.063889	0.099214	0.643946	0.5196
12 month lag	0.210648	0.098048	2.148427	0.0317**
18 month lag	0.237657	0.105789	2.246521	0.0247**
24 month lag	0.093347	0.103809	0.899220	0.3685
IAV(DV*no lag)	2.366534	0.667595	3.544862	0.0004***
IAV(DV*lag1)	-5.122286	0.932654	-5.492163	0.0000***
IAV(DV*lag2)	1.784806	0.526690	3.388719	0.0007***
IAV(DV*lag3)	-1.240421	0.407780	-3.041890	0.0024***
IAV(DV*lag4)	0.907595	0.406617	2.232063	0.0256**
IAV(DV*lag5)	-3.610618	0.656286	-5.501594	0.0000***
IAV(DV*lag6)	2.372685	0.489415	4.848006	0.0000***
IAV(DV*lag7)	-4.356359	0.822133	-5.298846	0.0000***
IAV(DV*lag8)	0.145905	0.872352	0.167255	0.8672
IAV(DV*lag9)	-0.130790	0.694946	-0.188202	0.8507
IAV(DV*lag10)	-0.784860	0.427687	-1.835127	0.0665*
IAV(DV*lag11)	-4.028295	0.784322	-5.136023	0.0000***
IAV(DV*lag12)	-2.365922	0.525457	-4.502597	0.0000***
IAV(DV*lag18)	-5.346763	0.836856	-6.389105	0.0000***
IAV(DV*lag24)	-3.686754	0.720239	-5.118793	0.0000***

IAV = interaction varible,
DV = dummy variable

Dep. variable:	DV_CHANGE_RATING
McFadden R-squared	0.204817
Log likelihood	-456.8600
Avg. log likelihood	-0.077434
Total obs	5900
Obs with Dep=0	5783
Obs with Dep=1	117

Appendix 9

Presented below is the interaction variable regression analysis table, based on an interaction variable considering downgrades, on a quarterly basis:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-2.967609	0.116654	-25.43941	0.0000
No lag	-0.057978	0.052874	-1.096539	0.2728
1 quarter lag	0.027211	0.055599	0.489417	0.6245
2 quarter lag	-0.055184	0.058694	-0.940199	0.3471
3 quarter lag	0.027770	0.062406	0.444985	0.6563
4 quarter lag	-0.007840	0.058972	-0.132948	0.8942
5 quarter lag	0.037466	0.060229	0.622064	0.5339
6 quarter lag	0.006432	0.060290	0.106685	0.9150
7 quarter lag	0.001842	0.058547	0.031457	0.9749
8 quarter lag	0.010769	0.054416	0.197911	0.8431
IAV(DV*no lag)	0.870594	0.212838	4.090403	0.0000***
IAV(DV*lag1)	-1.124957	0.248751	-4.522420	0.0000***
IAV(DV*lag2)	1.203180	0.308819	3.896072	0.0001***
IAV(DV*lag3)	1.131459	0.411705	2.748229	0.0060***
IAV(DV*lag4)	-0.073659	0.313884	-0.234670	0.8145
IAV(DV*lag5)	-1.374690	0.430537	-3.192962	0.0014***
IAV(DV*lag6)	-0.369468	0.368734	-1.001992	0.3163
IAV(DV*lag7)	-1.201484	0.323656	-3.712230	0.0002***
IAV(DV*lag8)	0.842781	0.361118	2.333811	0.0196**

IAV = interaction varible,
DV = dummy variable

Dep. variable:	DV_CHANGERATING
McFadden R-squared	0.108735
Log likelihood	-369.4812
Avg. log likelihood	-0.194464
Total obs	1900
Obs with Dep=0	1792
Obs with Dep=1	108

Appendix 10

Presented below is the interaction variable regression analysis table, based on an interaction variable considering upgrades, on a quarterly basis:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Intercept term	-3.022294	0.118017	-25.60902	0.0000
No lag	-0.042441	0.050793	-0.835583	0.4034
1 quarter lag	-0.088963	0.061243	-1.452624	0.1463
2 quarter lag	0.057016	0.063086	0.903779	0.3661
3 quarter lag	0.027652	0.066904	0.413304	0.6794
4 quarter lag	0.139932	0.063030	2.220103	0.0264**
5 quarter lag	0.055243	0.062511	0.883738	0.3768
6 quarter lag	0.094550	0.066172	1.428852	0.1530
7 quarter lag	0.005951	0.063196	0.094170	0.9250
8 quarter lag	0.083592	0.061049	1.369266	0.1709
IAV(DV*no lag)	-0.553189	0.231892	-2.385548	0.0171**
IAV(DV*lag1)	-0.691048	0.328423	-2.104139	0.0354**
IAV(DV*lag2)	-0.936523	0.287398	-3.258633	0.0011***
IAV(DV*lag3)	-0.395438	0.369415	-1.070443	0.2844
IAV(DV*lag4)	-1.110633	0.269062	-4.127799	0.0000***
IAV(DV*lag5)	-1.343160	0.356974	-3.762625	0.0002***
IAV(DV*lag6)	-0.334653	0.190883	-1.753185	0.0796*
IAV(DV*lag7)	-0.752610	0.360279	-2.088964	0.0367**
IAV(DV*lag8)	-1.397510	0.323453	-4.320602	0.0000***

IAV = interaction varible,
DV = dummy variable

Dep. variable:	DV_CHANGERATING
McFadden R-squared	0.185243
Log likelihood	-337.7642
Avg. log likelihood	-0.177771
Total obs	1900
Obs with Dep=0	1792
Obs with Dep=1	108

Artikeln är tänkt att vara en artikel i Aktiespararen. Den är därför skriven på ett sätt som vi tror skapar ett intresse hos en småsparare. Vi har också tittat på artiklar i Aktiespararen för att få en uppfattning om vilken längd (knappt 1000 ord) och form artikeln bör ha för att passa i Aktiespararen.

Slå marknaden med Mertonmodellen

Genom att förutse kreditbetygsförändringar med Mertonmodellen kan du som investerare ligga före marknaden och slippa onödiga förluster genom att justera ditt innehav i tid. Är du även mer riskbenägen kan modellen användas för att spekulera på marknaden för att nå överavkastning.

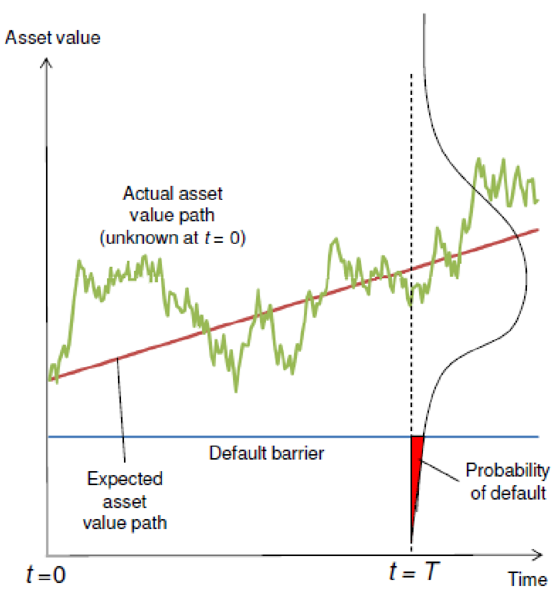
Att ligga före marknaden är alltid ett mål för investerare och för detta finns många tips. Dock finns ingen universallösning och det är ofta svårt att uppnå detta eftertraktade mål. En nyligen genomförd studie av Rebeggiani och Westerlund (2012) finner stöd för att en kreditvärderingsmodell av Merton kan indikera framtida kreditbetygsnedgraderingar. Detta kan ge investerare verktyget för att faktiskt ligga före marknaden. Eftersom tidigare forskning indikerar att marknaden reagerar starkt negativt på kreditbetygsnedgraderingar så kan en investerare som har förutsett detta inte bara undvika obehagliga överraskningar utan även göra spekulationsvinster genom att gå kort på marknaden.

Fördelen med modellen är att den bara använder sig av lättillgänglig data från publika aktiebolag vilket gör att den kan användas av småsparare med Excel-intresse. Bara publik data i form av historisk aktiekurs och bokföringsdata behövs till modellen. Detta används för att få fram marknadsvärdet för eget kapital och skulder vilket ger det totala marknadsvärdet på tillgångar. Utöver detta krävs ytterligare några variabler; exempelvis uppskattad framtida tillväxt, för att kunna räkna ut kreditrisken.

Kreditrisken är det som bestämmer avkastningen på en företagsobligation samt indikerar företagets förmåga att faktiskt betala räntorna till långivare. Alltså är det viktigt att du som investerare har koll på ett företags kreditvärdighet. Som nämnts tidigare i artikeln är det inte bara den absoluta kreditrisken som är av intresse utan även förändringar i ett företags kreditvärdighet på sikt eftersom det fungerar som en indikator på framtida kreditbetygsförändringar

Mertonmodellen uppskattar risken för att värdet på ett företags tillgångar understiger nominalvärdet på skulder och räntor som ska betalas under den tidshorisont som man är intresserad av, vanligtvis ett år. I och med detta får man ett mått på hur stor sannolikheten är för att ett företag ställer in sina betalningar inom en viss tid - kreditrisken. Förutom att man får ett mått på den absoluta kreditrisken kan man se trender i kreditrisken som kan orsaka kommande kreditbetygsförändringar.

Mertonmodellen, schematisk bild

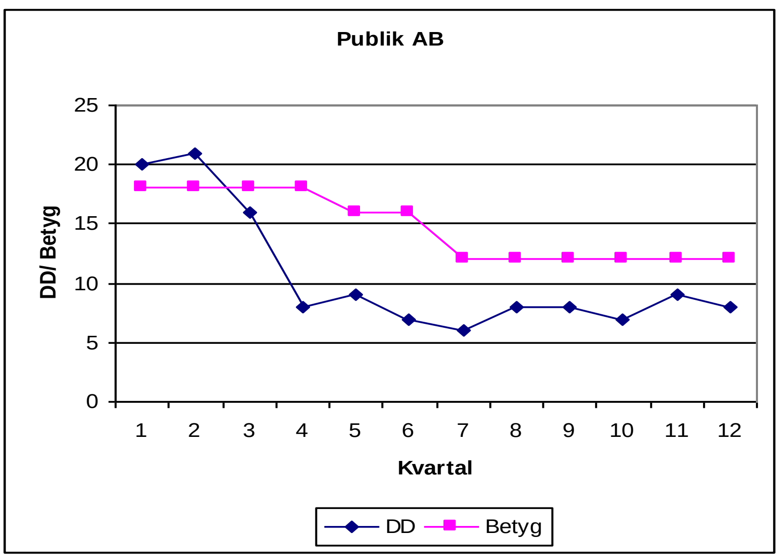


Mertonmodellen – Så funkar det

Modellen visar tidsförloppet ett år framåt. Den blå linjen visar summan av skulder och räntor som ska betalas inom ett år. Den röda linjen visar det förväntade värdet av tillgångarna (skulder + eget kapital). Den positiva lutningen beror på tillväxten i tillgångarnas värde. Den gröna linjen är en av många tänkbara utfall för tillgångarnas värde inom ett år och antar man att de här utfallen följer normalfördelningen får man fram hur stor del av utfallen som kommer att vara mindre än summan av skulder och räntor inom ett år – kreditrisken (det röda fältet i diagrammet).

Studien av Rebeggiani och Westerlund (2012) som har genomförts på ett större antal amerikanska företag visar att Mertonmodellen har en viss förklarande förmåga till kommande kreditbetygsförändringar och att fördröjningen i kreditbetygen är cirka ett år. Alltså ligger Mertonmodellen före kreditvärderingsinstituten och kan med viss precision indikera att en förändring sker i framtiden. När både uppgraderingar och nedgraderingar studerades tillsammans gav det dock ett svagt samband. Men när uppgraderingar och nedgraderingar studerades var för sig gav det ett mer intressant resultat. För kreditbetygsuppgraderingar kunde inget samband hittas men för kreditbetygsnedgraderingar blev sambandet starkare. Diagrammet nedan illustrerar sambandet som fanns i studien. Det visar hur Mertonmodellens mått (blå linje) börjar sjunka innan det verkliga kreditbetyget faktiskt gör det, alltså när det sker en nedgradering. Detta indikerar alltså en viss fördröjning hos kreditvärderingsinstituten, även känt som lagg.

Merton DD jämfört med betyg



(Diagrammet är endast illustrativt.)

Resultatet stödjer också tidigare forskning som påvisat att marknadsmodeller som Mertonmodellen kan förutse kreditbetygsförändringar och då framförallt nedgraderingar. Sambandet är alltså starkt på så sätt att olika undersökningar med olika företag och tidsram kommer fram till samma resultat.

Förutom att du som småsparare får en modell som kan hjälpa dig att öka din avkastning är det också en stor fördel att du på egen hand har möjlighet att göra en snabbvärdering av ett företags kreditvärdighet. Du slipper då att förlita dig endast på analytikers uppfattning, kreditvärderingsinstitut eller rådgivares tips. Detta kan vara bra eftersom det riktats stark kritik mot både kreditvärderingsinstitutens kreditbetyg och bankrådgivares tips. Dels gällande deras objektivitet dels gällande deras förmåga att på ett riktigt sätt återge kreditvärdigheten för olika företag.

Genom att lära sig grunderna i Mertonmodellen kan du som investerare utnyttja trögheten i kreditbetygen och tjäna pengar på detta men även bli mer självständig och få ett bra analysverktyg för investeringar och öka din förståelse för kreditrisk. Genom att en kreditbetygssänkning eventuellt kan förutses kan värdeförlust för investerare också i bästa fall undvikas.

Uppsatsen "Rating changes - Can they be predicted?" av Simone Rebeggiani och Marcus Westerlund (2012) finns tillgänglig på Lunds Universitets hemsida för den intresserade och ger läsare en inblick i Mertonmodellen och vilka möjligheter den erbjuder.