Probabilities of Default

A Comparison between the Merton DD Model and CDS contracts

Master Thesis

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Abstract

This study implements the Merton distance to default (DD) Model of Bharath (2008) to calculate credit default swap ("CDS" onwards) prices and compares these with prices of traded CDS contracts on the market. The Merton DD Model and CDSes are both measures that capture the probability of default for a certain firm. The sample is based on data available from Bloomberg consisting of 45 US listed firms with daily data from April 1, 2005 to June 30, 2016, covering different industries and all listed on an US based stock exchange. These firms all survived during the period of investigation. We find that CDS prices calculated with the Merton DD Model are significantly lower than prices of traded CDS contracts. The difference between the two prices is further investigated. Regressions containing industry, firm size, market-to-book ratio, and time effects are ran against a ratio capturing the difference. The difference between the two measures increases largely with firm size, while the market-to-book ratio has little impact on the difference. The results are robust over time and industries. Moreover, the credit rating of a firm has influence on the difference.

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I. INTRODUCTION

This study offers insights in the ability to estimate probabilities of default by comparing a model proven to be effective in earlier literature with actual prices from the market. The model that is the basis of this study is an interpretation of the structural Merton Model that measures credit risk. Bharath (2008) develops the Merton DD Model to find a probability of default by first determining a distance to default with the Merton Model. The Merton Model as described by Merton (1974) uses the Black-Scholes Model, treating equity as a call option, the face value of debt as the strike price, and the underlying asset as firm value. The Merton Model calculates the credit spread on debt, estimated by the risk-neutral probability that a company will default. There are two types of implementation considered in this research, namely by Jones, Mason and Rosenfeld (1984) and by Hull, Nelken and White (2004). Our study investigates a dataset of 45 firms over a period of eleven years, the long period distinguishes the study from the previously mentioned literature. Moreover, the dataset includes all the firms listed in the US that have enough data available to implement our model. Bharath (2008) has tested the Merton DD Model by comparing its results with Moody's KMV probabilities, Cox hazard models and spreads on bond prices and CDSes. The Moody's KMV Model is based on a model that is a generalization of the Merton model that allows for various classes and maturities of debt and uses a large historical database instead of the cumulative normal distribution to convert distances to default into default probabilities. Hazard models are reduced-form forecasting models that have been recently applied by a number of authors. This study is comparing the outcomes of the Merton DD Model with the prices of traded CDS contracts, where the underlying asset is firm value. The CDS market is known to be a changing market, since it became widely known in the beginning of the 21st century. Some people (including Grol and Kuppeveld, 2015) argue that there is a transition to a new CDS market currently going on, although this may take some time.

CDS contracts were introduced as an insurance offering against default in 1997. According to Grol and Kuppeveld (2015) the CDS market has shrunk with 75 percent since its peak in 2007. Since the sub-prime housing crisis in 2008 regulation has been tightened, which made CDSes more expensive. Next to the higher prices, clearing has reduced the outstanding amount of swaps, since now opposing positions can offset each other. Moreover, the most complex derivatives have just disappeared. Grol and Kuppeveld (2015) argue that, although the market has shrunk enormously in the recent years there is still demand. The market today is more transparent and has much less counterparty risk, which makes experts think that the downturn is only temporary.

This study aims to investigate the difference between the probability of default derived by the Merton DD Model with the probability of default derived from traded CDS contracts. Additionally, other risk factors that might influence the relationship between the Merton DD Model and traded CDSes, of the type typically used in equity pricing studies as introduced by Elton et al. (2001) and Campello et al. (2008) are investigated. These additional risk factors are industry, firm size, and the market-to-book ratio. Moreover, it will be investigated if the difference is time-specific as suggested by Hull et al. (2004).

If CDS prices calculated using the Merton DD Model are equal to the prices of actual traded CDS contracts this would mean that CDS contracts are a direct measure of default and that it would be possible to estimate the probability of default for every firm given that all the information needed as input for the Merton DD Model is available. Researches as Longstaff, Mithal and Neis (2005), Blanco, Brennan and Marsh (2005), and Ristolainen (2015) use CDS contract information as direct measures for the size of default- and non-default components in corporate yield spreads. Other literature finds evidence that there are more components in CDS contracts. Elton, Gruber, Agrawel and Mann (2001) find that a large part of the CDS spread remains unexplained, where the vast majority is believed to be compensation for systematic risk. This is supported by Campello, Chen and Zhang (2004), who identify this additional risk as the type typically used in equity pricing studies.

After constructing the theoretical framework, chapter three will give insights in the methodology. The chapter will start of with a short explanation of how the dataset was defined and what sources where used. The methodology consists of three parts. First the probability of default is calculated using the Merton DD Model. Second, the calculated probabilities are recalculated into CDS prices, so that the calculated CDS prices are compared to CDS prices from the market. Finally, several regressions are ran to see what characteristics influence the differences that are found.

The study finds that CDS prices derived using the Merton DD Model are lower than market prices, which indicates that they consist of more components than only default risk or that the Merton DD Model does not fully represent default risk. The difference between the two measurements for default probability is influenced by firm- and time specific factors. The difference between the two measures increases with firm size. The effect of firm size becomes larger if rating dummies are added to the regression. This means that the difference between the two measures is larger for bigger firms with a higher rating. We find that a firm's market-to-book ratio has a relatively small increasing influence on the difference between the two measures. Time or industry differences do not change the probability of default any more than already included in stock prices. The rating of a firm has impact on the influence that the size of the firms has, however there is no effect on the influence of the market-to-book ratio.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Credit risk is related to the risk of default. Yields on corporate bonds are higher than yields on treasury bonds to compensate for credit risk. The credit spread is the difference between the yield on a corporate bond and the yield of a treasury bond, both bonds should have the same maturity if they are being compared (Elton et al., 2001).

Rating agencies as Moody's and Standard & Poor's provide credit ratings. Companies pay these rating agencies to get a rating on the company itself or on its bonds. The ratings are split in ordinal categories ranges from C to triple A and can be divided into two groups, namely investment grade (triple B and up) and speculative grade or junk (everything below triple B). These ratings are correlated with the probability of default and with credit spreads and they provide information over and above publicly available information.

A credit spread compensates for the expected loss on a risky bond consisting of default probability and expected recovery rate, and depends on the credit rating and the maturity of the bond. Credit spreads typically increase with maturity, except for highly speculative bonds, in this case the probability gets smaller over a longer horizon. The spreads depend on characteristics of the issuer, are variable over time, and they increase in recessions. Further, the spreads also differ over sectors, for example, the spreads in the financial sector are larger than the spreads in the health care sector. According to Duffee (1998) credit spreads are negatively correlated with risk-free interest rates.

Introduction to the Merton Model

Gupton, Kocagil and Liu (2007) argue in their report written for Fitch Ratings that credit risk models can be classified into two groups, known as structural models (Black & Scholes, 1973, and Merton, 1974) and reduced form models (Jarrow-Turnbull, 1995, and Duffie-Singleton, 1999).

In 1974, Merton introduced a model that calculates the credit spread on debt using the Black-Scholes Model, where equity is treated as a call option, the face value of debt can be seen as the strike price, and the underlying asset is firm value. The model estimates the probability that a company will default, implying a certain credit spread on debt. This probability can either by a risk-neutral or a real world probability, depending on the drift term of firm value. Merton (1974) assumes that a company defaults if the value of assets is smaller than the promised debt repayment at time T. The literature defines two ways to implement the Merton Model. The first way is presented by Jones et al. (1984). They test the predictive power of the Merton Model of typical capital structures, while making a distinction between investment grade and non-investment grade bonds. Moreover, they deal with the issue of the assumption of the Merton Model that assumes that the firm only has issued one callable zero-coupon bond maturing in T periods that raises some difficulties implementing the model. Another issue they are dealing with is that, different from one debt issue, multiple debt issues can interact amongst optimal call policies of different bonds. The paper refers to Jones et al. (1983) that states that it is necessary to choose the capital structure that will result in the maximum value of equity in order to identify the optimal call policy. According to Jones et al. (1984) there should be two optimal capital structures if the state of an all equity firm is considered. It is argued that multiple possibilities in capital structures can be ruled out based on rational theorems which show that certain kinds of bonds are always called first.

The dataset of Jones et al. (1984) consists of a total of 27 firms from January 1975 through January 1981 on a monthly basis chosen based on certain criteria. First, the firms should have a simple capital structure, meaning that there is only one type of stock (no preferred stock), there are no convertible bonds, and there is a small number of debt issues. Second, there is only a small proportion of private debt to total capital. Third, there is only a small proportion of short term notes payable or capital leases to total capital. Last, all publicly traded debt should be rated. There are three kinds of data used as input for the model, namely covenant data, standard deviation data, and interest rate data. The standard deviation is based on a monthly time series for the value of the firms using 24 months of historical data, and is based on the relationship between the standard deviations of the return on assets and the return on equity of the firms.

The second way to implement the Merton Model is introduced by Hull, Nelken and White. In 2004, they suggest a new way of implementing the Merton Model (1974) based on Geske (1979). Different from Black-Scholes, Geske (1979) uses a variance of the rate of return on the stock that is not constant, since leverage effects are incorporated into the option pricing. Instead of being contant, the variance is a function of the level of the stock price. This method avoids the mapping of all the payments to a certain debt maturity date as seen before by Jones et al. (1984), creating a linkage between credit and options and allowing credit spreads to be estimated directly from implied volatility data. The dataset of Hull et al. (2004) consists of a total of 325 firms over a period of one year. This new approach is particularly appropriate for firms that are known to have significant off-balance-sheet liabilities, since these liabilities might not be taken into account in the traditional approach. Hull et al. (2004) find that their approach outperforms the simple version of the traditional implementation of the Merton Model (1974). They also find that the relationship between the Merton Model and CDS spreads might be different for different firms by plotting implied spreads and CDS spreads for different firms. Elaborating on this they think that it is possible that macro-economic variables cause the relationship between the two spreads to change over time.

Introduction to the Merton DD Model

Bharath (2008) introduces the Merton DD Model based on Merton (1974). The model is tested in different ways. First, the Merton DD probabilities are compared to Moody's KMV probabilities. Moody's KMV uses the, what they call, KV model. This model is a generalization of the Merton (1974) model that, in contrast to the original model, does allow for various classes and maturities of debt. Instead of using the cumulative normal distribution to convert the distance to default into a probability of default, Moody's KMV uses its large historical database to estimate the distribution of changes in distances to default and calculates the probability of default based on that distribution. Moody's KMV also makes adjustments to the accounting information that they use to calculate the face value of debt, which cannot be replicated because the information is unavailable. Second, a Cox hazard model is employed to assess the Merton DD Model. Hazard models are applied by Shumway (2001) and Chava and Jarrow (2004), arguing that these models are superior to other types of models because of three reasons. First, they resolve problems of static models for forecasting bankruptcy by explicitly accounting for time. Bankruptcy occurs infrequently. The characteristics of most firms change from year to year, while static models can only consider one set of explanatory variables for each firm over several years. Second, hazard models incorporate time-varying covariates, or explanatory variables that change over time. Another reason why hazard models are preferred is that they calculate probabilities of default by using out-of-sample data, which can be done without estimating actual default probabilities. Finally, Bharath (2008) tests the Merton DD Model by regressing the probabilities of default on CDS spreads and on spreads of bond prices.

Introduction to the probability of default

The probability of default depends, just as the credit spread, on the credit rating. The probabilities vary over time as well, partly because of the economic climate, GDP growth, and average maturity of bonds. Longstaff et al. (2005) use CDS contract information to find direct measures for the size of default- and non-default components in corporate yield spreads. Credit derivatives only have begun trading actively in the past several years, wherein CDSes are the most common type of credit derivatives. Both Longstaff et al. (2005) and Bharath (2008) describe a CDS contract similar to an insurance contract compensating the buyer for losses arising from a default. The buyer of a CDS pays a fixed fee each period to the seller until either default occurs or the swap contract matures. In return, the seller has the obligation to buy back the defaulted bond at its par value if the underlying firm defaults on its debt. The fee paid by the buyer is called the credit default swap premium and is typically quoted in basis points per $100 of notional amount. Because of the full protection the buyer receives against the credit risk of the underlying asset, there is a very close relationship between the CDS price and bond spreads according to Blanco et al. (2005) and Ristolainen (2015). Contrary to bonds, CDSes are very liquid. Blanco et al. (2005) and Longstaff et al. (2004) find that CDS spreads are much lower than corporate bond spreads. According to them, this can be explained by tax and liquidity effects that are included in bond premiums, while CDSes only measure default risk. In a like manner, Ristolainen (2015) argues that it is possible to extract default probabilities from CDS spreads, as it is seen as a function of the probability of default and the recovery value.

Elton et al. (2001) define three components of the spreads in rates, namely expected default loss, tax premium and risk premium. They argue that the tax premium should be included, since corporate bonds have to offer a higher pre-tax return than government bonds to yield the same after-tax return. Elton et al. (2001) find that only a small part of the spread is defined by the expected default loss. Differential taxes have a more important influence on spreads. However, the largest part of the differential remains unexplained, where the vast majority is believed to be compensation for systematic risk. They argue that the corporate bond spread may reflect additional risk factors as well, of the type typically used in equity pricing studies, this is supported by Campello et al. (2004). Even though these results seem to contradict the findings of Longstaff et al. (2005) and others, they are more similar than expected, since the expected default loss and the risk premium defined by Elton et al. (2001) are taken as the default risk by Longstaff et al. (2005).

The importance of liquidity risk, which is defined as the ease with which stocks are traded by Brunnermeier and Pedersen (2009), on stock returns has been a much discussed topic in asset pricing studies. De Jong and Driessen (2012) expect corporate bonds to be exposed to liquidity shocks in both the stock and the bond market, since there is a correlation between returns on corporate bonds and both the returns on the treasury bond market (default-free bonds), as well as with returns on the stock market (Kwan, 1996). They consider the liquidity risk originating from the equity market and the liquidity risk from the treasury bond market as two different types. Several studies (Amihud & Mendelson, 1986; Brennan and Subrahmanyam, 1996; Amihud, 2002; Acharya and Pedersen, 2005; Hasbrouck, 2009) support the idea of De Jong and Driessen (2012) that both expected and unexpected liquidity affects expected returns in the stock markets in order to compensate for higher transaction costs on securities that are illiquid.

Next to using CDS premiums directly as a measure of the default component Longstaff et al. (2005) use another approach to define the default component in corporate bond swaps. In their second approach they employ a, in their own words: “well-known reduced-form framework of Duffie (1998), Lando (1998), Duffie and Singleton (1997, 1999), and others” as a measurement of the size of the default component by capturing any liquidity or other non-default related components in corporate bonds prices. Ristolainen (2015) finds that the liquidity of a CDS contract may have a lowering effect on the CDS price, which is similar to Longstaff et al. (2005) found in their second approach. This finding is later confirmed by Arakelyan and Serrano (2012) who find that CDS illiquidity contributes to higher CDS spreads. Tang and Yan (2010) state that investor sentiment is the most important determinant of credit spreads at market level. Moreover, they think that firm-specific cash flow characteristics have explanatory power.

Research question

Based on the information we have found in the literature, we are interested in the probability of default as calculated by the Merton DD Model developed by Bharath (2008). Are the CDS prices derived from the model aligned with CDS prices trading on the market? Additionally, we want to find out whether there are additional risk factors influencing the relationship between the Merton DD Model and traded CDSes, of the type typically used in equity pricing studies as introduced by Elton et al. (2001) and Campello et al. (2008). To find the answer to this matter we have prepared the following research question:

Which firm characteristics are related to the difference between the probability of default derived by the Merton DD Model with the probability of default derived from traded credit default swaps the smallest?

We expect to answer this question through the following sub-questions:

a) Does industry affect the difference between the two measures?
b) Does firm size affect the difference between the two measures?
c) Does the market-to-book ratio affect the difference between the two measures?
d) Does calendar time affect the difference between the two measures?

Hypotheses

The following hypotheses have been developed regarding the research question and its sub-questions. These hypotheses are in line with our expectations of the outcome of this study based on the previously treated literature review.

H1. We expect that the probability of default using the Merton DD Model differs from the probability of default derived from market credit default swaps.

Literature suggests that CDS contracts are not a direct measure of the probability of default (Longstaff et al. (2005), among others). According to recent empirical evidence credit risk factors related to the underlying company do not fully explain CDS spreads (Collin-Dufresne, Goldstein, & Spencer Martin, 2001, Blanco et al., 2005, Tang & Yan, 2010, among others). Collin-Dufresne et al. (2001) even find that only about one quarter of the variation in credit spreads explains default risk. Apart from default risk, literature finds some other factors that affect the CDS price. Arakelyan and Serrano (2012) and Ristolainen (2015) suggest that liquidity is an important element, while Tang and Yan (2010) see more importance in investor sentiment in determining CDS prices at market level. Together with Hull et al. (2004) they think that there are some firm-specific characteristics with explanatory power.

H2. We expect that the difference between the two probabilities of default is significantly influenced by certain characteristics of the firm or the industry (Hull et al., 2004, Tang & Yan, 2010). We want to investigate what effect additional risk factors from equity pricing studies (Elton et al., 2001, & Campello et al., 2008) as industry, firm size, and market-to-book ratio have on the expected difference between the two measures.

Campello et al. (2008) developed an approach based on the Merton Model recognizing that equity and debt are contingent claims written on the same assets. Therefore, they must share similar common risk factors. Moreover, they think it is useful to investigate bonds instead of equity, since bond yield spreads contain forward-looking risk premiums beyond expected default loss, rather than past information. Campello et al. (2008) find support to Fama and French (1993, 1996) that size and book-to-market factors are priced risk factors. They find no evidence that momentum is priced. Moreover, the market beta is significantly priced in their cross-sectional regressions.

According to Shalit and Sankar (1977) the choice for a particular measure of firm size depends on the purpose of the study. In their study they conducted a valid statistical test to provide future investigators with relevant information for choosing an appropriate size variable and they find the highest correlation coefficient between assets and stockholders' equity. Based on the study of Shalit and Sankar, that is later supported by evidence of Fama and French (1992, 1993), we think that stockholders' equity, or the firm's market capitalisation is the best measurement to measure size. Fama and French (1992) find that two variables, market capitalisation and the book-to-market ratio capture much of the cross-section of average stock returns, which are used as an input for the Merton DD Model. Later, in 1993, they confirm their theory by developing a three-factor asset-pricing model that seems to capture the cross section-of average returns of US stocks. Since these factors are affecting stock prices we expect they also affect the CDS price.

We expect that non-cyclical industries might result in a higher difference between the probabilities of default, since they are proven to be less volatile, and therefore less risky. Under the same reasoning we expect that large firms and firms with a low market-to-book ratio would result in a higher difference between the models.

Additionally, we expect that the difference is time specific, as supported by Hull et al. (2004) who find that that it is possible that the relationship changes over time due to macro-economic variables.

III. RESEARCH METHOD

Selection of the data

The initial sample was based on data available ten years ago from Bloomberg consisting of 156 US listed firms with daily data from April 1, 2005 to June 30, 2016, covering different industries and all listed on an US based stock exchange. These firms all survived during the period of investigation, therefore there is probably some selection bias in the dataset. Share prices, CDS spreads are extracted from Bloomberg over the period. Balance sheet data, income statement, the risk-free rate, and shares outstanding are extracted from Thomson Reuters' Datastream. All the information is stated in US dollars.

To clean the dataset, the assumptions of Jones et al. (1984) are used. First all firms having preferred shares of convertible bonds are removed from the dataset to create a simple capital structure. We assume that these listed firms have only a small proportion of private debt to total capital. Private debt here is assumed to be debt provided by individuals or private businesses. Thereafter, firms are left out if the proportion short term notes payable to total capital is too big, this happens when the payables over sales are higher than 20 percent. Further, it is assumed that all publicly traded debt of the firms is rated. Finally, firms with lots of missing data are removed from the dataset. At the end, the dataset consists of 47 US listed firms with daily data over the period ranging from 2005 to 2015. These firms included firms over ten different industries as defined by the MSCI industry index, which are the following: consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, telecommunication services, and utilities.

The Merton DD Model

This research implements the Merton DD Model described by Bharath (2008) to find the probability of default using stock prices. The model estimates a probability of default for each firm in the sample at any given point in time. The model calculates a z-score, also called the distance to default, by subtracting the face value of the firm's debt from an estimate of the market value of the firm. Then, the difference is divided by an estimate of the volatility of the firm. The z-score is shown in a cumulative density function to calculate the probability that the value of the firm will be less than the face value of its debt at the forecasting horizon. It is assumed that the equity of the firms receives no dividend and debt is a pure zero-coupon discount bond. If at time T, the asset value is below promised debt repayment, the firm defaults.

The market value of debt is estimated using the classic Merton (1974) bond pricing model. This model makes two important assumptions. The first assumption assumes that the total value of a firm follows a geometric Brownian motion:

$$dV = \mu V dt + \sigma_V V dW$$

Where V is the total value of the firm, μ is the continuously compounded expected return on the total value, σ_V is the annual volatility of firm value, and dW is a standard Wiener process. The second important assumption is that the firm only has issued one zero-coupon bond maturing in T periods.

Under these assumptions equity looks like a call option on the underlying assets of the firm with a strike price equal to the promised debt payment, or the face value of the firm's debt and a time-to-maturity of T. We can use a model similar to the Black-Scholes to determine the value of equity as a function of the total value of the firm. Bharath (2008) introduces the Black-Scholes-Merton Formula, expressing the value of equity at time t as a function of the value of the firm.

$$E_t = VN(d_1) - N(d_2)Fe^{-rT} \tag{1}$$

Where E is the market value of the firm's equity, V equals firm value, and N is the cumulative standard normal distribution function. F equals the face value of the firm's debt, or the promised debt repayment. This study uses the book value of the firm's total liabilities as the face value of debt, which include Current Liabilities, Long Term Debt, Deferred Taxes, Deferred Income, Other Liabilities, and some industry specific journals. Finally, r is the current risk-free interest rate. d_1 and d_2 are calculated by:

$$d_1 = \frac{\ln\left(\frac{V}{F}\right) + \left(\mu + \frac{\sigma_V^2}{2}\right)T}{\sigma_V\sqrt{T}}$$

$$d_2 = d_1 - \sigma_V\sqrt{T}$$

T is the forecasting horizon in years, which is assumed to be one year in this study. σ_V equals the annual volatility of the firm value during the event period covering the last ten workdays of each year. The Merton DD Model is calculated using an event window of eleven working days at the end of each year in the dataset. At the end, when the probabilities of default are calculated an average value for the probability of default is used to continue with our other models.

Another important equation relates the volatility of the firm's value to the volatility of its equity as shown by Jones et al. (1984). Since V follows a geometric Brownian motion, it follows from rewriting the formula that (Goswin, n.d.):

$$\sigma_E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial V}\sigma_V$$

Combining this formula with the Black-Scholes-Merton Models gives:

$$\sigma_E = \left(\frac{V}{E}\right)N(d_1)\sigma_V \qquad (2)$$

Given equations (1) and (2) the risk-neutral probability that a firm will default by time T is the probability that shareholders will not exercise their call option on the underlying assets of the firm for the promised payment at time T. The Merton DD Model uses the Black-Scholes-Merton equation and the equation above to translate the value and volatility of a firm's equity into an implied probability of default. The model observes the value of the option as the total value of equity of the firm, which is easy observable in the marketplace by using stock prices multiplied by shares outstanding. The equity volatility is estimated from daily historical stock returns coming from an estimation period of 150 working days for each year ranging from 2005 to 2015 ending twenty working days before the event period, and converted into annual figures.

Crosbie and Bohn (2003) explain that market leverage moves far too much in practice to get reasonable results from equation (2). This problem can be solved by implementing an iterative procedure introduced by Crosbie and Bohn (2003) and Vassalou and Xing (2004) by solving the equations (1) and (2) for values of the total value of the firm and the volatility of firm value after gathering the values for each of the variables mentioned before. Unless specified otherwise, in the rest of the paper values of πMerton are calculated by following this iterative procedure.

Goswin (n.d.) defines a method using equity values and equity volatilities under the simplifying assumption that leverage is constant. He argues that this simplified method differs from the iterative approach, because the latter changes in leverage, while the simplified approach does not.

Since we are estimating the probability over a period over five years we do not expect that leverage remains constant. Therefore, we prefer the iterative approach.

To calculate the distance to default the values of V and σ_V resulting from earlier calculations can be implemented in the following:

$$DD = \frac{\ln\left(\frac{V}{F}\right) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{3}$$

Where μ is an estimate of the expected annual return of the firm's assets by defining an assumption. In this study, μ is set equal to the risk-free rate, since we do not want to inflate the results. This equation depends on three input variables, namely the firm's face value of debt, the volatility of the firm's assets, and an assumption about the expected annual return of the firm's assets. In order to compare the Merton DD Model with CDS spreads it is necessary to find a credit spread implied by the Merton Model to make the outcome comparable. The probability of default can be calculated by multiplying the negative value of the distance to default with the cumulative standard normal distribution function:

$$\pi_{Merton} = N\left(-\left(\frac{\ln\left(\frac{V}{F}\right) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)\right) = N(-DD) = 1 - N(d_2) \tag{4}$$

Which again, depends on three input variables and π_{Merton} equals the cumulative probability of the firm defaulting within the coming five years. π_{Merton} equals one minus the cumulative standard normal distribution function of d_2.

Probability of default from CDS spreads

As mentioned in the literature review, credit ratings provided by rating agencies are correlated with credit spreads. The probability of default depends, just as the credit spread, on the credit rating. These variables vary over time, partly because of the economic climate, GDP growth, and average maturity of bonds.

Hull (2012) provided data presenting cumulative default rates for each rating and with different term structures showing that investment grade bonds hardly ever default within one year and that triple A bonds are not expected to default at all in the first three years, which is displayed below:

Cumulative Default Rates

RATING \ TERM	1	2	3	5	10	15	20
AAA	0.000	0.000	0.000	0.10	0.52	0.99	1.19
AA	0.008	0.019	0.042	0.18	0.52	1.11	1.93
A	0.021	0.095	0.22	0.47	1.29	2.36	4.24
BBB	0.18	0.51	0.93	1.94	4.64	8.24	11.36
BB	1.21	3.22	5.57	10.21	19.12	28.38	35.09
B	5.24	11.30	17.04	26.79	43.43	52.17	54.42
CCC	19.48	30.49	39.72	52.62	69.18	70.87	70.87

Table 1. Cumulative default rates for each rating and with different term structures

Compared to the probabilities provided by Hull (2012), the Merton DD Model underestimates the probability of default, especially for the first five years as supported by Jones et al. (1984), Ogden (1987) and Leland (2004). In the long run, we expect that the model overestimates this probability, since it is based on a cumulative normal distribution. We chose to use a 5 year CDS spread as we believe these CDSes are traded the most and represent the most accurate estimation for the probability of default.

Recalculate CDS prices using the Merton DD Model

Having calculated the probability of default using the Merton DD Model, CDS data will be used to test whether the probability of default calculated by the model is significantly different from the actual probability of default, like has been done in earlier research of Berndt, Douglas, Duffie, Ferguson & Schranz (2004) and Longstaff et al. (2005). The information given by CDSes can be used as measure of default probabilities that are comparable with the probability estimates obtained by the Merton DD Model. To compare the historical CDS prices obtained from Bloomberg with the calculated default probabilities the CDS prices are recalculated using the obtained probabilities from the model. To calculate these probabilities a few assumptions have to be made, for simplicity: defaults always happen halfway through the year, and CDS payments are made once a year at the end of each year. Given these assumptions the present value of the payments made on the CDS assuming a notional principal of $1 is given by:

$$P = \sum_{t=1}^{t=T} \left(1 - \pi_{Merton,1}\right)^{t} e^{-rt} + \left(1 - \pi_{Merton,1}\right)^{t-1} \pi_{Merton,1}\, e^{-r(t-0.5)} 0.5s$$

Where s is the CDS spread, which is the amount paid per year as a percentage of the notional principal. T is the life of the CDS contract, which equals five years in this study.

As described by Bharath (2008), the first term in the equation calculates the present value of the expected payments made at the end of each year until period t, and the second term calculates the present value of the accrual payments that happen in case a default occurs halfway through the year. If an assumption is made about recovery of the CDS the expected present value of the payoff is given by the following equation:

$$P = \sum_{t=1}^{t=T} \left(1 - \pi_{Merton,1}\right)^{t-1} \pi_{Merton,1} (1 - R)\, e^{-r(t-0.5)} \tag{5}$$

Where π_{Merton} equals the probability of default as calculated in the Merton DD Model. The Merton DD Model has calculated a five-year cumulative probability of default, while equation (5) needs the probability of default for each year. To align the data, it is assumed that the five-year probabilities are linearly ascending, therefore the cumulative five-year probability π_{Merton} should be divided by five in order to get to $\pi_{Merton,1}$. We also assume that the risk-free rate is r with continuous compounding. Furthermore, R equals the recovery rate. To value the payoff of the CDS an implied estimate of recovery rate is needed (Bharath, 2008). Berndt et al. (2004) suggest a recovery rate of 25 percent, although it is relatively low compared to history. According to Bharath, Hull, Predescu, and White (2004) argue that the value of a CDS is not very sensitive to the recovery rate, because implied probabilities of default are approximately proportional to 1/(1–δ) and the payoffs from a CDS are proportional to (1–δ). At the end, the outcome of equation (5) needs to be multiplied by thousand, since CDSes come in batches of 1000 USD.

This study uses the probabilities calculated before using the Merton DD Model to find CDS prices for the data. The CDS data obtained from Bloomberg is not complete for the whole dataset, but the sample of 47 firms is still usable for the purpose of this paper.

Find influence of firm characteristics

Hull et al. (2004) find that the relationship between the Merton Model and CDS spreads might be different for different firms or time, due to changing macro-economic variables. Moreover, Elton et al. (2001) and Campello et al. (2008) believe that there are systematic risk factors that are used in equity pricing that have influence. Therefore, we develop a model that investigates the differences between CDS prices depending on several firm-specific variables, such as industry, firm size, and market-to-book ratio, to further investigate previous findings. Moreover, we investigate time-effects.

Once the prices using the Merton DD Model have been calculated and compared with CDS prices from the market we are interested in how the differences between the two are dependent on several characteristics that are mentioned before, namely time, industry, size, and market-to-book ratio. To find the origin of the differences it is necessary to run a regression. In the following equations a ratio calculated by dividing the calculated CDS price by their market prices is regressed against the characteristics, rating dummies, and some fixed effects for time, industry and firm.

$$Y_{i,t} = \beta_1 + \beta_2 \times Log(Market\ Capitalisation)_{i,t} + \beta_3 \times MTB_{i,t} + \varepsilon_{i,t}$$

$$Y_{i,t} = \beta_1 + \beta_2 \times Log(Market\ Capitalisation)_{i,t} + \beta_3 \times MTB_{i,t} + \beta_4 \times Year\ FE_{i,t} + \varepsilon_{i,t}$$

$$Y_{i,t} = \beta_1 + \beta_2 \times Log(Market\ Capitalisation)_{i,t} + \beta_3 \times MTB_{i,t} + \beta_4 \times Industry\ FE_{i,t} + \varepsilon_{i,t}$$

$$Y_{i,t} = \beta_1 + \beta_2 \times Log(Market\ Capitalisation)_{i,t} + \beta_3 \times MTB_{i,t} \\ + \beta_4 \times YearTimesIndustry\ FE_{i,t} + \varepsilon_{i,t}$$

$$Y_{i,t} = \beta_1 + \beta_2 \times Log(Market\ Capitalisation)_{i,t} + \beta_3 \times MTB_{i,t} + \beta_4 \times AAA \\ - AA\ Rating\ Dummy + \beta_5 \times A\ Rating\ Dummy + \beta_6 \times BBB\ Rating\ Dummy \\ + \beta_7 \times BB\ Rating\ Dummy + \beta_8 \times B - CCC\ Rating\ Dummy + \varepsilon_{i,t}$$

Where Y equals the ratio of P over CDS to investigate the difference between the two measures, Log(Market Capitalisation) is equal to the market value of Equity of the firm, and MTB is the market-to-book ratio of the firm. Furthermore, several fixed effects are in the different regressions.

IV. RESULTS

By having a first look at the data using scatter plots, Appendix A, there is a small correlation recognizable. We will test the data using different variations to find which variables influence the correlation between the probabilities of default coming from the Merton DD Model and the ones from CDS prices.

Summary Statistics

VARIABLES	(1) N	(2) mean	(3) median	(4) sd	(5) min	(6) max
Market Cap	517	42.11	25.65	47.51	0.062	260.9
Sales	515	48.50	25.22	70.78	2.025	485.7
MTB	517	6.00	2.73	61.12	-107.90	1,382.26
Rf	517	0.0305	0.0295	0.0101	0.0177	0.0462
CDS	401	82.26	51.64	101.25	6.86	812.57
P	513	41.27	2.76	85.15	0.00	481.79
Log Market Cap	517	17.05	17.06	1.06	11.03	19.38
Log Sales	515	17.07	17.04	1.08	14.52	20.00
P/CDS	515	0.36	0.06	0.68	0.00	6.42

Table 2. Summary Statistics

Detailed Summary Statistics

VARIABLES	(1) p1	(2) p5	(3) p10	(4) p25	(5) p50
Market Cap	17.37	4.03	7.81	13.72	25.65
Sales	3.80	5.55	7.06	10.46	25.22
MTB	0.479	0.899	1.141	1.637	2.734
Rf	0.0177	0.0177	0.0193	0.0215	0.0295
CDS	8.844	14.28	18.71	31.32	51.64
P	1.84e-07	4.87e-05	0.00155	0.0936	2.755
Log Market Cap	14.37	15.21	15.87	16.43	17.06
Log Sales	15.15	15.53	15.77	16.16	17.04
P/CDS	1.06e-09	2.69e-07	1.79e-05	0.0021	0.0595

Table 3. Bottom Percentiles of the Variables

Detailed Summary Statistics

VARIABLES	(1) p50	(2) p75	(3) p90	(4) p95	(4) p99
Market Cap	25.65	48.57	95.33	168.51	214.31
Sales	25.22	58.04	108.70	171.50	421.85
MTB	2.734	3.975	6.383	10.01	20.40
Rf	0.0295	0.0415	0.0441	0.0462	0.0462
CDS	51.64	92.15	157.6	232.5	557.3
P	2.755	34.34	148.8	236.5	399.5
Log Market Cap	17.06	17.70	18.37	18.94	19.18
Log Sales	17.04	17.88	18.50	18.96	19.86
P/CDS	0.0595	0.4160	1.1057	1.5950	2.8204

Table 4. Upper Percentiles of the Variables

Variable definitions
Market Cap = Market Capitalisation in Million USD
Sales = Sales in million USD as from Thomson Reuters
MTB = Market-to-Book Ratio as from Thomson Reuters
Rf = Risk-free rate based on 10-year US bonds
CDS = CDS Prices in USD as from Bloomberg
P = Calculated CDS Prices in USD

The summary statistics in tables 2 up to and concluding 4 show some negative values for the Market-to-Book Ratio variable. Having a closer look at the data it shows that the firms with these negative ratios show a very high CDS price as downloaded from Bloomberg, which means that these firms are likely to default. On the other hand, the same firm also shows the highest values of the Market-to-Book Ratio, which tells us that this firm is probably very volatile. The firms with a negative Market-to-Book Ratio, which are two, are deleted from the dataset. After deleting these firms the maximum value for the Market-to-Book Ratio equals 39.61. Moreover, the tables show that for the variables Market Cap, Sales, MTB, CDS, and P the median is much lower than the mean indicating that the data is skewed to the right. With this, it can be better estimate whether a given future data point will be higher or lower than the mean. The skewness can be solved for the Market Cap and Sales by taking the logarithm, which is shown in Appendix B as well.

Appendix B reports the distribution of the MSCI industries over the firms of the dataset. The initial sample consists of the 156 US listed firms initially downloaded, covering the different industries, which are all listed at either the New York Stock Exchange, or the NASDAQ. The second pie chart shows the industry distribution of the sample after it has been cleaned by deleting firms with data insufficient to reproduce the model. Overall, the distribution shows no significant deviations from the initial distribution. Though it can be seen that in the final sample consumer staples, health care, industrial, and telecommunication services firms might be overrepresented, while financial firms might be underrepresented. The changes are considered to be relatively big if the amount in percentage of firms in the industry changes over 50 percent with regards to the initial dataset. For the industries information technology, telecommunication services, and utilities there remains a small amount of firms in the final dataset, namely only one or two.

T tests

We performed several two-sided t tests to compare the means of the downloaded CDS prices with the calculated CDS prices. In these t tests we test the following hypothesis: $H_0: CDS - P = 0$. If the prices statistically differ the t value should be higher than the z for a certain confidence interval. The t values of the tests are listed in the tables 5 up to and including 8 below, as well as the probabilities for the tested hypothesis and the differences between the two measures.

Based on the data it can be concluded that the CDS prices calculated by the Merton DD Model are statistically significantly higher than the CDS prices as retrieved from Bloomberg, meaning that CDS contracts in the market are priced too low according to the Merton DD Model.

Table 5 on the next page and a look at the scatter plots in Appendix A show relatively different spreads in the CDS prices or 2008 than in other years. The reason for this can be the financial sub-prime housing crisis that took place that year, though this result is not significant. Another possible reason is that the liquidity of the CDS market was higher in this year. It is noticeable that the difference between the two measures has increased after from 2010. The reason for this might be that the liquidity of the CDS market has decreased due to the crisis, and therefore CDS prices are higher.

Two sample t test

YEAR	Average CDS-P	T value	CDS-P=0
Overall period	41.43	10.7744***	0.0000
2005	29.59	2.5852***	0.0137
2006	19.19	3.2340***	0.0025
2007	41.16	6.5006***	0.0000
2008	-11.65	-0.1843	0.8548
2009	39.62	3.3618***	0.0018
2010	61.31	8.7306***	0.0000
2011	68.76	3.1402***	0.0033
2012	73.03	6.7926***	0.0000
2013	50.70	6.1323***	0.0000
2014	37.51	9.2099***	0.0000
2015	49.62	4.0737***	0.0008

Significance level
*** 99%, **95%, *90%

Table 5. Two sample t test to test whether P is equal to CDS

Having a closer look at the difference on an industry level in table 6 hereafter there are also different spreads, however not significant, for the financial industry. Here, the same reasoning can be used as for 2008, namely that the financial sub-prime housing crisis might have impacted the outcome of the t tests, though not significant, or that liquidity is high.

There is no market CDS data available for the industries information technology and utilities in our dataset, therefore we cannot make any statements about these industries. Most industries show a relatively equal difference between the two measures. Only the telecommunication services industry shows a very high difference. Our dataset contains little data of this industry, which might either mean that the CDS market of this industry is illiquid and therefore market prices are higher, or there is not enough evidence to make a statement about this industry.

Two sample t test			
INDUSTRY	Average CDS-P	T value	CDS-P=0
Consumer Discretionary	31.25	5.5983***	0.0000
Consumer Staples	63.40	9.0183***	0.0000
Energy	35.88	2.8420***	0.0081
Financials	0.53	0.0259	0.9799
Health Care	18.10	2.6202***	0.0114
Industrials	31.85	4.9664***	0.0000
Information Technology	n.a.	n.a.	n.a.
Materials	31.41	3.1868***	0.0046
Telecommunication Services	170.01	4.2985***	0.0004
Utilities	n.a.	n.a.	n.a.

Significance level
*** 99%, **95%, *90%

Table 6. Two sample t test by industry to test whether P is equal to CDS

The different levels of size and market-to-book ratios below all show that the calculated CDS price is significantly lower than the market CDS price.

Two sample t test			
SIZE	Average CDS-P	T value	CDS-P=0
Small	58.58	6.4982***	0.0000
Medium	37.69	8.2316***	0.0000
Big	32.86	6.8895***	0.0000

Significance level
*** 99%, **95%, *90%

Table 7. Two sample t test by size to test whether P is equal to CDS

Two sample t test			
MTB	Average CDS-P	T value	CDS-P=0
Low	28.18	2.7360***	0.0077
Mid	-5.12	5.6757***	0.0000
High	43.00	10.8758***	0.0000

Significance level
*** 99%, **95%, *90%

Table 8. Two sample t test by Market-to-Book Ratio to test whether P is equal to CDS

Table 8 shows that for firms with a median Market-to-Book Ratio market CDS prices are lower than CDS prices as calculated by the Merton DD Model. We cannot find a reason for this difference. Table 9 gives an indication about the relation of the difference between the two measures and the credit rating. It suggests that the difference between the calculated CDS price and the market CDS price gets larger if the credit rating decreases. For all the ratings, the calculated CDS price is significantly lower than the market CDS price. The difference is the largest for firms with a BB rating.

Two sample t test

RATING	Average CDS-P	T value	CDS-P=0
AAA-AA	21.86	3.5305***	0.0014
A	18.49	4.6983***	0.0000
BBB	43.76	9.3876***	0.0000
BB	310.11	5.1454***	0.0009
B-CCC	174.48	2.9879***	0.0203

Significance level
*** 99%, **95%, *90%

Table 9. Two sample t test by Credit Rating to test whether P is equal to CDS

Finally, the dependent variable that will be used in the regressions has been tested for the hypothesis $H_0: Y = 1$ in table 10 and is statistically significantly smaller than one for all the years, except for 2008, where the ratio is significantly higher than one. This is in line with findings of the tests that were performed earlier. Moreover, the ratio is very small for the years following 2008. This means that the difference between the two measures is larger, which aligns with the average differences in table 5.

Two sample t test			
YEAR	Average P/CDS	T value	Y=1
Overall period	0.36	-18.7924***	0.0000
2005	0.30	-4.3023***	0.0001
2006	0.45	-3.0786***	0.0039
2007	0.23	-15.6410***	0.0000
2008	1.29	2.2217**	0.0325
2009	0.48	-5.0186***	0.0000
2010	0.18	-21.7525***	0.0000
2011	0.54	-6.2426***	0.0000
2012	0.07	-45.7547***	0.0000
2013	0.03	-75.8798***	0.0000
2014	0.02	-140.000***	0.0000
2015	0.31	-7.9421***	0.0000

Significance level
*** 99%, **95%, *90%

Table 10. Two sample t test to test whether P/CDS is equal to one

Regressions

Now that our hypothesis that the CDS prices calculated using the Merton DD Model are lower than CDS prices traded in the market has been confirmed by the data it might be relevant to find out what effect each of the selected characteristics has on the calculation of the CDS price. In Appendix E, the results of regressions ran against a ratio of P divided by CDS, where P is de calculated CDS price and CDS is the price as found on the market.

Table 11 shows the outcomes shows regressions performed on only the intercept. It can be concluded that there is a relatively large amount of explanatory power in the model.

Regression with Fixed Effects

DEPENDENT VARIABLE	(1) Ratio	(2) Ratio	(3) Ratio	(4) Ratio
Constant	0.3609***	0.3609***	0.3609***	0.3609***
	(0.0360)	(0.0316)	(0.0354)	(0.0318)
Observations	377	377	377	377
R-squared	0.0000	0.2480	0.0499	03950
Adj. R-squared	0.0000	0.2275	0.0319	0.2209
Number of categories		11	8	85
Year FE		YES		
Industry FE			YES	
Year-Times-Industry FE				YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 11. Regression of an intercept and fixed effects against a ratio of P/CDS

Regression of Characteristics with Fixed Effects

DEPENDENT VARIABLE	(1) Ratio	(2) Ratio	(3) Ratio	(4) Ratio
Logarithm of Market Cap	-0.1804***	-0.1358***	-0.1773***	-0.1178***
	(0.0336)	(0.0308)	(0.0363)	(0.0348)
Market-to-Book Ratio	-0.0393***	-0.0303**	-0.0274*	-0.0143
	(0.0145)	(0.0131)	(0.0158)	(0.0154)
Constant	3.5648***	2.7742***	3.4729***	2.4147***
	(0.5649)	(0.5192)	(0.6097)	(0.5881)
Observations	377	377	377	377
R-squared	0.1057	0.3039	0.1272	0.4224
Adj. R-squared	0.1010	0.2810	0.1058	0.2511
Number of categories		11	8	85
Year FE		YES		
Industry FE			YES	
Year-Times-Industry FE				YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 12. Regression of different characteristics against a ratio of P/CDS using fixed effects

Though the industry dummies add value to the outcome of the regressions, the results of their betas are not statistically significant (Appendix C). This might be due to the numbers of firms included in the dataset, which are 47. When these firms are spread over ten industries there will be only one to thirteen firms in each industry. Further research should include more firms in each of the industries to draw a significant conclusion on this subject. There are three industries that are left out of the regressions, because of multicollinearity reasons. The industries that are left out are: information technology, telecommunication services, and utilities. These industries are only represented by one or two firms each in the dataset, which might be the reason that multicollinearity is occurring. Furthermore, these three industries are all non-cyclical, and may therefore show some resemblances. Despite the fact that the results are not statistically significant all the industries are showing a relatively large positive effect on the ratio, except for materials that has a relatively smaller effect and consumer staples that has a small negative effect. This means that most industries decrease the increase between P and CDS. Although the results indicate that there might be an influence on the ratio depending on different industries, there are no significant results to draw a conclusion.

By adding year dummies to the regression you can see that there is a small explanatory effect. The result for 2008 shows a very strong statistically significant positive effect on the ratio of P over CDS, which is higher than one. Although not significant, table 1 in Appendix C shows also a result for 2008 very different from the other years. Having a closer look, most of the effects are positive, except for 2012 and 2013. 2014 has been left out of the regressions, due to multicollinearity reasons, possibly because there is not much data for this year in the dataset. 2006, 2009 and 2011 have a relatively large statistically significant positive effect on the ratio. This confirms the expectation as introduced by Hull et al. (2004) who think that it is possible that macro-economic variables cause the relationship between the two spreads to change over time.

Finally, we added five rating dummies. The ratings are clustered into groups the following: AAA-AA, A, BBB, BB, and B-CCC. The ratings are determined based on the S&P rating of the firms in the dataset during the period from January 2006 to December 2015 as from Compustat. The rating that occurred the most during the sample period of ten years is used as the rating of the firm. The dummy for AAA-AA has been left out of the regression due to multicollinearity reasons. In Appendix C it can be seen that the rating of a firm has a large effect on the coefficient for size and the intercept, who almost double compared to the other regressions. The effects are the largest and significant for the higher ratings AAA-A.

The results of the constant and the coefficient of market capitalisation are highly significant. Beta estimates of between -0.12 and -0.19 for the log market capitalisation imply that a 100% increase in the size of a firm would on average lead to a -12% to -18% (decrease) in the ratio of P over CDS, meaning that the difference between the two measures increases. By adding year and industry fixed effects the estimates do not change much, which indicates that the results are robust over time and over industries. If rating dummies are added the coefficient for the log market capitalisation decreases to -0.30, meaning that the difference between the two measures even increases more when rating dummies are added, namely the ratio is increasing with 30% for a 100% increase in the size of a firm. This finding confirms our expectations based on research of Campello et al. (2008). Moreover, Campello et al. (2008) find that the market beta is significantly priced in their cross-sectional regressions, even after controlling for size, book-to-market, and prior returns. These results contradict expectations based on Fama and French (1992), who find that the market beta has no significant effect. To control for this finding we added a market factor based on the MSCI USA in the regressions. There is no effect on the coefficients of the factors, the intercept, or on the Adjusted R-squared. The coefficient for the market beta is large, but not significant.

There is a small negative statistically negative effect found for the effect of the market-to-book ratio. The regressions show that the coefficient found is small: a 100% increase in the market-to-book ratio of a firm would on lead to a -1% to -4% (decrease) in the ratio of P over CDS. The results indicate that the market-to-book ratio has not a large influence on the difference between the probabilities of default derived by equity prices with the probabilities of default derived from credit default swaps. As for the size factor, this finding aligns with our expectations.

According to the Adjusted R-squared 30 percent of the relationship between the characteristics and the ratio is explained by the model. This complements our earlier finding that the CDS prices calculated using the Merton DD Model are significantly smaller than CDS prices in the market. There could be more omitted variables ending up in the error term driving the relationship between the characteristics and the ratio. The Adjusted R-squared only increases if the added independent variables really enhance the model, unlike the R-squared. It can be seen that year fixed effects add great value to the regression, since they increase the adjusted R-squared by 0.18, while industry fixed effects barely increase the adjusted R-squared. The rating dummies increase the Adjusted R-squared with 0.04.

V. CONCLUSION

The Merton DD Model is used to calculate CDS prices using market stock prices of 47 US listed firms over a period of eleven years, then the outcomes are compared to real CDS prices downloaded from Bloomberg. The Merton DD Model is a model developed by Bharath (2008) based on the Merton Model (1974). The model estimates a probability of default for each firm in the sample at any given point in time by calculating the distance to default and converting this to a probability of default. By comparing the outcomes of this model with the market CDS prices the calculated prices are strongly statistically significantly lower than the prices of traded CDS contracts. Therefore, it can be concluded that the price of a CDS contract does not fully consist of the probability of default or that the Merton DD Model is a correct method to calculate the probability of default. This is in line with earlier literature where several other components are mentioned that can possibly affect CDS prices, examples are liquidity, investor sentiment, and the expected recovery rate.

The difference between the two measures might differ due to firms-specific characteristics or macro-economic variables as found in earlier research (Elton et al., 2001, Hull et al., 2004, & Campello et al., 2008). This research investigated the effects of industry, size, market-to-book, and time characteristics on the size difference between the two measures of CDS prices.

The difference between the two measures increases with firm size. This implicates that there are more or larger additional risk factors influencing the price of traded CDS contracts for bigger firms. The effect of firm size is even larger if rating dummies are added to the regression, meaning that the difference between the two measures is larger for bigger firms with a higher rating. We find that a firm's market-to-book ratio gives little information about its influence on the difference, but the effect is negative. Meaning that the difference between the two measures increases with the market-to-book ratio. Time or industry differences do not change the probability of default any more than already included in stock prices. The rating of a firm has impact on the influence that the size of the firms has, however there is no effect on the influence of the market-to-book ratio. The findings for firm size and the market-to-book ratio align with the research of Campello et al. (2008) who find that size and book-to-market as typically used in equity pricing studies are priced risk factors for bonds. We find no evidence that the market beta is priced in the regressions. Adding this factor will have no impact on the conclusions, which is contrary with the findings of Campello et al. (2008), but in line with Fama and French (1992). Moreover, we found that the lower the credit rating of a firm, the less bias there is in the Merton DD Model.

In the end, about one third of the variation in the CDS prices is explained by the probability of default. This is in line with earlier research where only about one quarter of the variation in credit spreads explained default risk. Further research can find where the difference between default risk and traded CDS prices is coming from. Here it might be interesting to investigate the effect of liquidity or investor sentiment.

Some industries and years have a relative effect on the difference between the Merton DD Model prices and market CDS prices, but these findings are, especially for the industries, not significant. Further research might be able to confirm this suggestion by using a larger dataset with enough firms for each industry. This study finds that the size and the market-to-book ratio of the firm matters in determining a probability of default using the Merton DD Model. This conclusion contributes about one third of the difference, therefore there should be other, probably firm-specific, characteristics that affect the difference. These characteristics probably can be found in characteristics that influence the cash flows or risk premiums.

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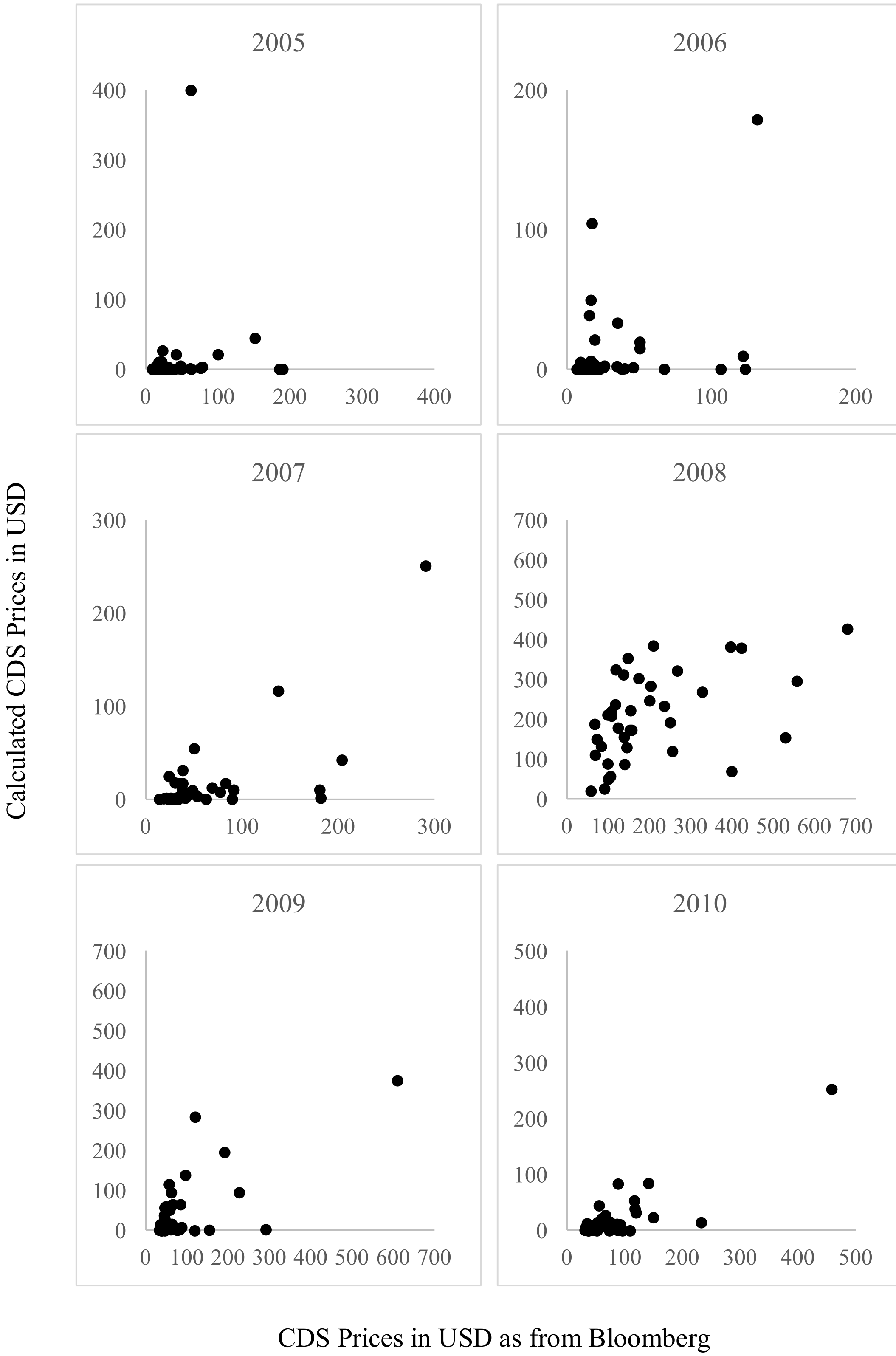
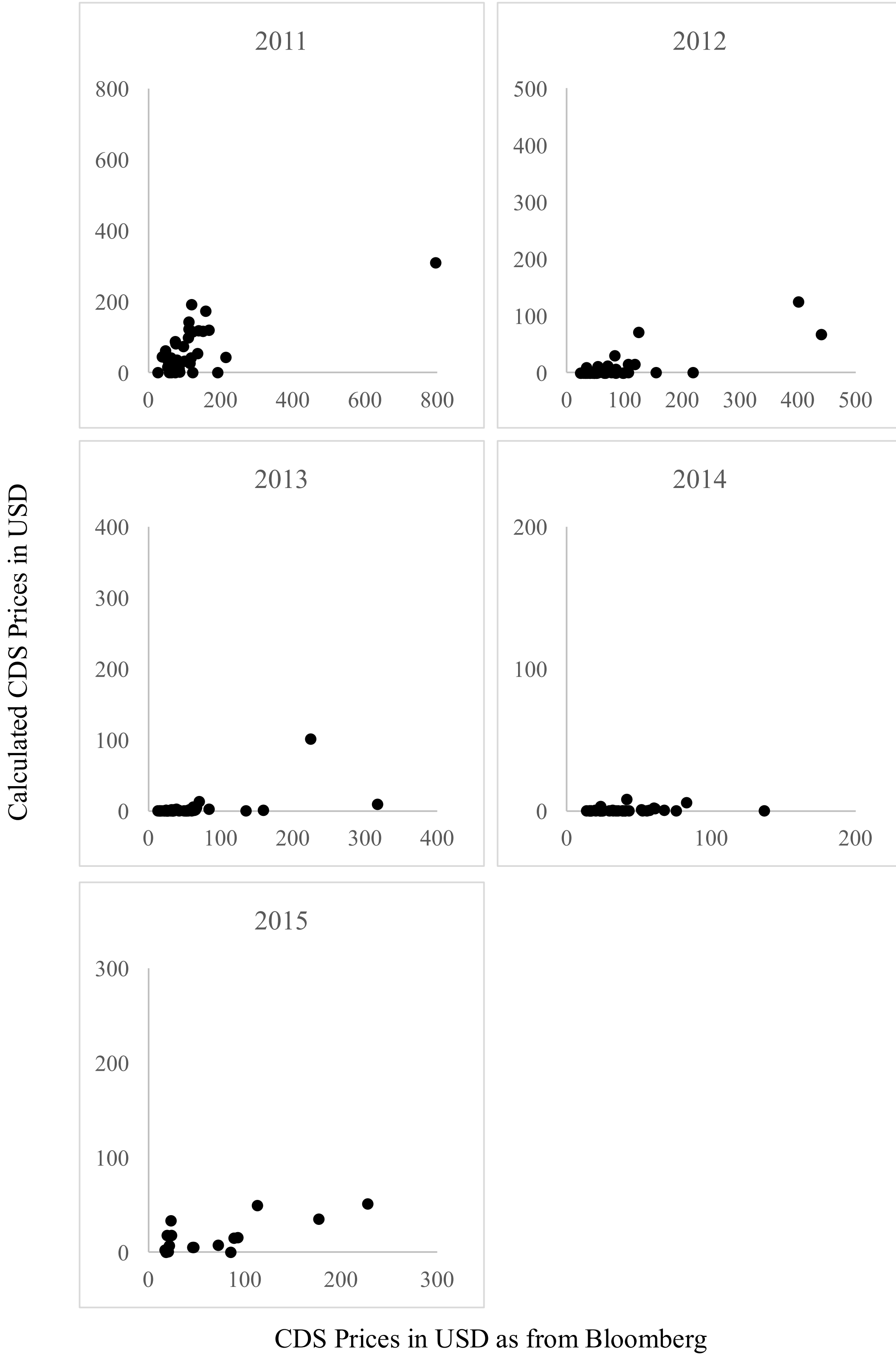
APPENDICES

Appendix A: Overall scatter plots

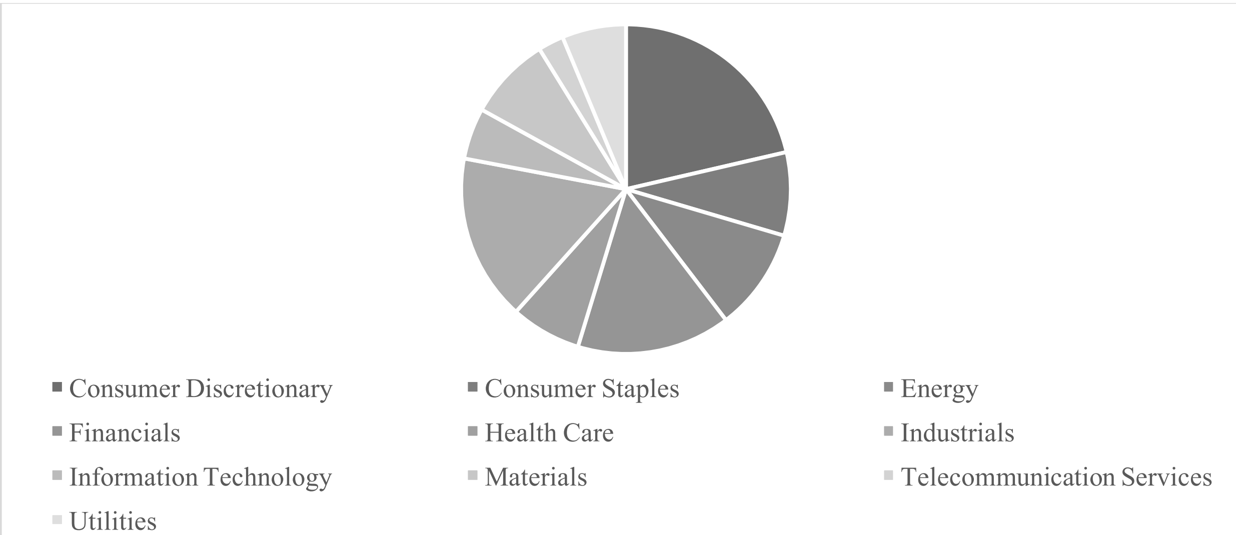



2011
800
600
400
200
0
0
200
400
600
800
2012
500
400
300
200
100
0
0
100
200
300
400
500
2013
400
300
200
100
0
0
100
200
300
400
2014
200
100
0
0
100
200
2015
300
200
100
0
0
100
200
300
Calculated CDS Prices in USD
CDS Prices in USD as from Bloomberg

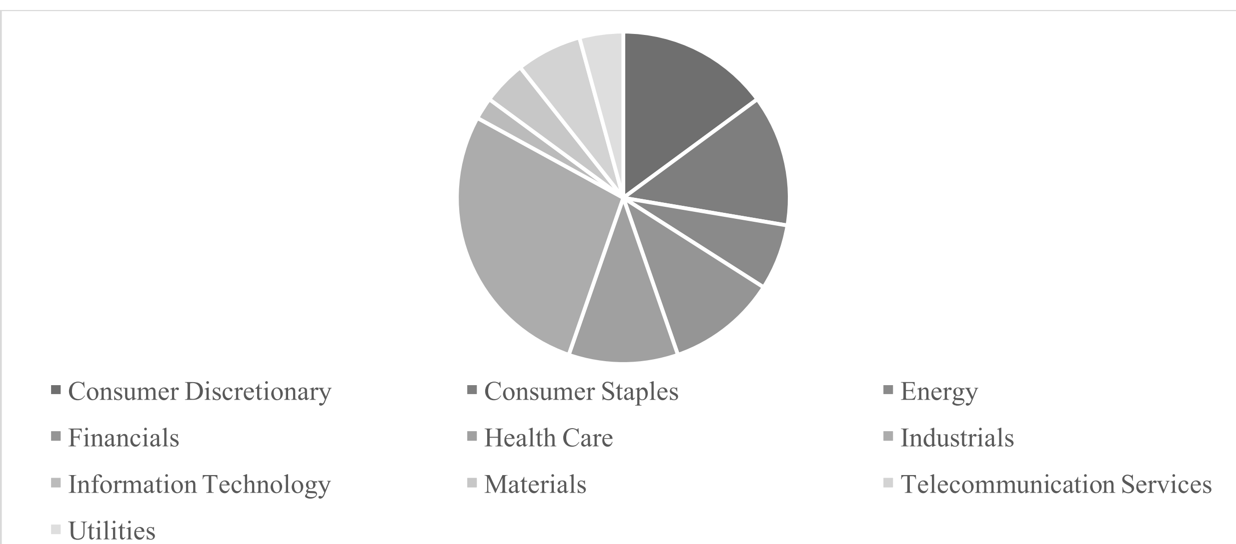
Appendix B: Industry distribution of the data

Most firms of the dataset are listed on the New York Stock Exchange. There are four firms, of a total of 47, that are listed on the NASDAQ. This Appendix shows how the firms are distributed over the different MSCI industries.

<u>Initial dataset</u>



<u>Final dataset: after adjusting for missing data etc.</u>



Appendix C: Regression outcomes using dummy variables

Regression of Characteristics using Dummies

DEPENDENT VARIABLE	(1) Ratio	(2) Ratio	(3) Ratio	(4) Ratio	(5) Ratio
Logarithm of Market Cap	-0.1804***	-0.1773***	-0.1358***	-0.3035***	-0.2286***
	(0.0336)	(0.0363)	(0.0308)	(0.0458)	(0.0572)
Market-to-Book Ratio	-0.0393***	-0.0274*	-0.0303**	-0.0258*	-0.0082
	(0.0145)	(0.0158)	(0.0131)	(0.0146)	(0.0147)
D1		0.1646			-0.0826
		(0.1721)			(0.2168)
D2		-0.0053			-0.2638
		(0.1778)			(0.2281)
D3		0.3021			0.0303
		(0.1908)			(0.2254)
D4		0.1908			-0.1567
		(0.2581)			(0.2860)
D5		0.2891			-0.0543
		(0.1765)			(0.2386)
D6		0.2182			-0.0348
		(0.1638)			(0.2137)
D7		Omitted			Omitted
D8		0.0430			-0.2755
		(0.2138)			(0.2600)
D9		Omitted			Omitted
D10		Omitted			Omitted
D2005			0.1380		0.1298
			(0.1468)		(0.1472)
D2006			0.3014**		0.3050**
			(0.1464)		(0.1460)
D2007			0.0998		0.1007
			(0.1459)		(0.1453)
D2008			1.0905***		1.0604***
			(0.1489)		(0.1521)
D2009			0.3146**		0.3002**
			(0.1479)		(0.1491)
D2010			0.0291		0.0307
			(0.1472)		(0.1471)
D2011			0.4045***		0.3953***
			(0.1459)		(0.1457)
D2012			-0.0419		-0.0352
			(0.1454)		(0.1441)

D2013			-0.0338		-0.0123
			(0.1454)		(0.1434)
D2014			Omitted		Omitted
D2015			0.2041		0.1747
			(01797)		(0.1772)
DR1				Omitted	Omitted
DR2				-0.0258	-0.0275
				(0.1402)	(0.1433)
DR3				-0.3662**	-0.2072
				(0.1552)	(0.1690)
DR4				-0.8276***	-0.7657**
				(0.2717)	(0.3773)
DR5				-0.8594***	-0.5212
				(0.3238)	(0.3452)
Constant	3.5648***	3.3033***	2.5428***	5.8663***	4.2878***
	(0.5649)	(0.6527)	(0.5462)	(0.8466)	(1.1923)
Observations	377	377	377	377	377
Adjusted R-squared	0.1057	0.1272	0.3039	0.1527	0.3470
Adj. R-squared	0.1010	0.1058	0.2810	0.1389	0.3045
Industry Dummies		YES			YES
Year Dummies			YES		YES
Rating Dummies				YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 1. Regression of different characteristics against a ratio of P/CDS

Variable definitions
Market Cap = Independent Variable Market Capitalisation in Million USD
MTB = Independent Variable Market-to-Book Ratio as from Thomson Reuters

D1 = Dummy for Consumer Discretionary Industry
D2 = Dummy for Consumer Staples Industry
D3 = Dummy for Energy Industry
D4 = Dummy for Financials Industry
D5 = Dummy for Health Care Industry
D6 = Dummy for Industrials Industry
D7 = Dummy for Information Technology Industry
D8 = Dummy for Materials Industry
D9 = Dummy for Telecommunication Services Industry
D10 = Dummy for Utilities Industry

D20XX = Year Dummy

DR1 = Rating Dummy for AAA-AA
DR2 = Rating Dummy for A
DR3 = Rating Dummy for BBB
DR4 = Rating Dummy for BB
DR5 = Rating Dummy for B-CCC