STOCKHOLM SCHOOL OF ECONOMICS
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Prediction of default

A comparison of the ability of credit ratings and credit default swaps to predict default in financial companies

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Abstract

This thesis compares the ability of credit default swaps and credit ratings to estimate probability of default in the financial sector by examining 40 European and US based financial companies during the period June 30, 2006 to June 30, 2009. No statistically significant difference is found between the two methods in the default probabilities given to the companies in the sample. Further, no statistically significant difference is found for either method in the probabilities of default given to the group of companies defaulting during the period of study compared to the group of companies not in default. The intergroup risk assessment of credit ratings and credit default swaps is, however, found to be statistically different.

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TABLE OF CONTENTS

1. INTRODUCTION

Problem Area

During the last year the world has experienced a financial crisis dwarfing everything seen in modern financial history. The underlying reasons are probably to be debated for decades to come but some areas are more frequently pointed out than others. One of them is the responsibility of the rating agencies, especially as a catalyst for the financial turmoil. The three most renowned of them, Standard & Poor’s, Moody’s and Fitch, have run into difficulties when giving ratings to many financial companies and assets that, with hindsight, seem to have been overoptimistic.

At the same time, the credit default swap (CDS) truly bloomed. CDS is a financial instrument that enables lenders to insure themselves against the risk of debtor default. The lender buys protection from a protection seller that ensures that in case the reference entity (the debtor) defaults, the protection seller will make the protection buyer (the lender) good. Indirectly, the price of a CDS can be seen as the risk for financial distress the market believes the reference entity faces. Given a credit rating for a specific company and a secondary market for CDS, there are two views on a company’s future creditworthiness and probability of default, which can be compared and contrasted.

Purpose and question

Due to the complexity of financial companies, investors often seek guidance in terms of the creditworthiness of such companies. In the ongoing crisis, established models have failed to correctly assess the probability of default in financial companies and there is consequently a need to evaluate these methods. One such established model is credit ratings, which have been widely used for decades. CDS, on the other hand, is a relatively new phenomenon. Through the credit rating and the CDS, investors are given two views on risk, and even though both credit ratings and CDS are highly accessible, their ability to assess probability of default has never been thoroughly compared.

Several interesting questions arise; is there a difference in the risk the rating agencies and the CDS market anticipates for companies in the financial sector and is it possible that the market is more efficient than the rating agencies in estimating the risk for default in financial companies? Also, is the relatively new instrument CDS influenced by credit ratings in its assessment of risk? This thesis examines this topic by comparing and contrasting the ability of credit ratings and CDS to assess the probability of default. The focus of the study is i) to examine whether credit ratings or CDS are more successful in assessing the probability of default in financial companies; ii) to evaluate the ability of credit ratings and CDS to distinguish between companies subsequently in default and companies that remain going concerns; iii) to find out to what extent CDS rely on credit ratings for risk assessment. By doing so, the authors hope to fill a gap in the research field of risk estimation.

2. CREDIT DEFAULT SWAPS

Credit derivatives

CDS belong to a family of financial instruments called credit derivatives (Fabozzi, Davis & Choudry, 2006). Credit derivatives exist to protect against the risk that financial obligations are not fulfilled. They deal with the credit risk if a lender cannot honour its obligations. In other words, credit derivatives are performance guarantees. Credit derivatives make sure that an investor does not need to worry whether the counterparty is going to be there when the payments are due. They make sure that the payments will be performed, if not by the counterparty then by the credit derivative seller. There are seven kinds of credit derivatives:

- Index swaps
- Basket default swaps
- Asset swaps
- Total return swaps
- Portfolio/ synthetic collateralized debt obligations
- Credit-linked notes
- CDS

CDS in detail

A CDS has two active parties, the protection seller and the protection buyer, plus a reference entity (Durbin, 2006). The reference entity has no interest in the CDS contract, but its actions will affect the protection seller and the protection buyer. The reference entity has a financial obligation towards the protection buyer. The protection buyer wants an insurance against financial distress in the reference entity, and receives this by purchasing a CDS from the protection seller. In case the reference entity does not manage to honour its obligations, the protection seller will step in and make the protection buyer good. For this, the protection seller receives a quarterly fee, also known as a spread. The CDS spread is not a spread per se, but a premium that the protection buyer pays based on the notional value of the financial obligation. Finally, the protection seller and the protection buyer agree on what events will trigger the contract. Common triggers are given in the 1999 ISDA Credit Derivatives Definitions (Fabozzi, 2006):

- Bankruptcy
- Credit event upon merger
- Cross acceleration
- Cross default
- Downgrade
- Failure to pay
- Repudiation/moratorium
- Restructuring of debt obligations

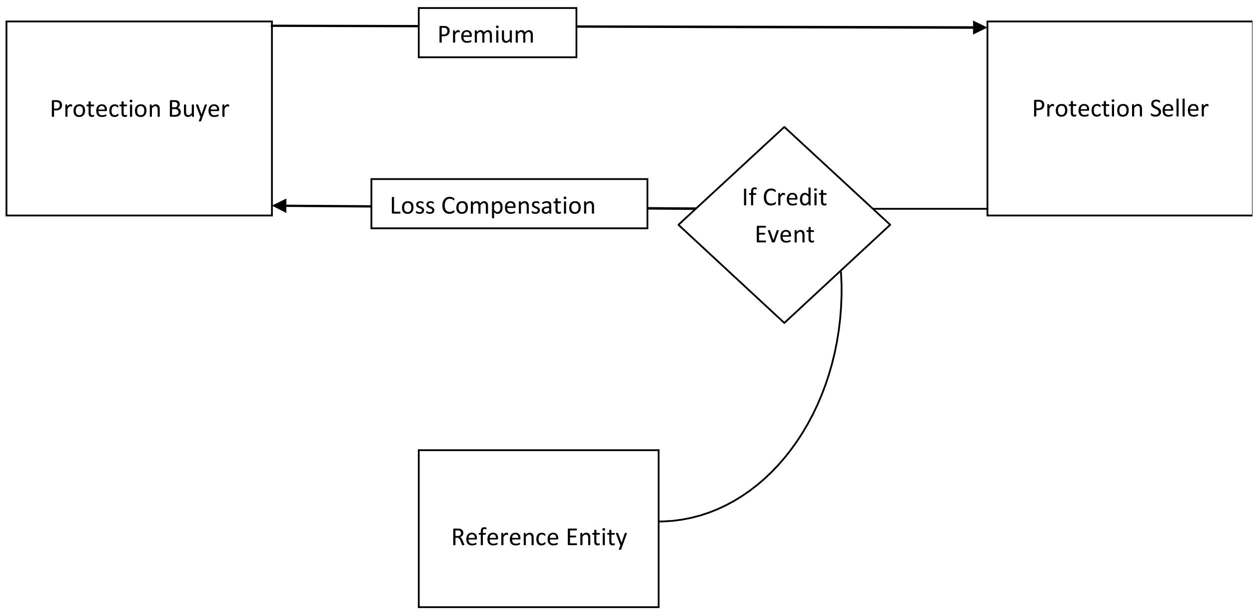
Trigger events and maturity dates

What trigger events are included differ from contract to contract, but generally it is in the protection buyers interest to include as many as possible whereas the protection seller wants to minimise the number of trigger events. The credit default spread can be seen as a measure of how likely it is, as seen by the market, that the reference entity will get into financial distress. If one of the trigger events occurs, the protection seller must do either a cash settlement or a physical settlement, depending on the type of contract. A cash settlement means that the net loss is compensated. If, for example, only 50 percent of the value of the financial obligation can be restored, the protection seller gives the remaining 50 percent cash to the protection buyer. With a physical settlement, the protection seller will buy the entire obligation for its notional value from the protection buyer. The net values of the methods are the same. (Figure 1).

Just as the underlying loan has a maturity date, the CDS has a maturity date. It means that the protection buyer has protection during a certain period of time. Since many contracts are individualised, the contracts active period can differ in infinite ways, but the most common time period is five years. Three year and one year contracts are common too.

CDS are also referred to as single-name CDS. The name comes from that it has only one reference entity, whereas other credit derivatives can have several or follow an index.

Figure 1: **CDS structure**



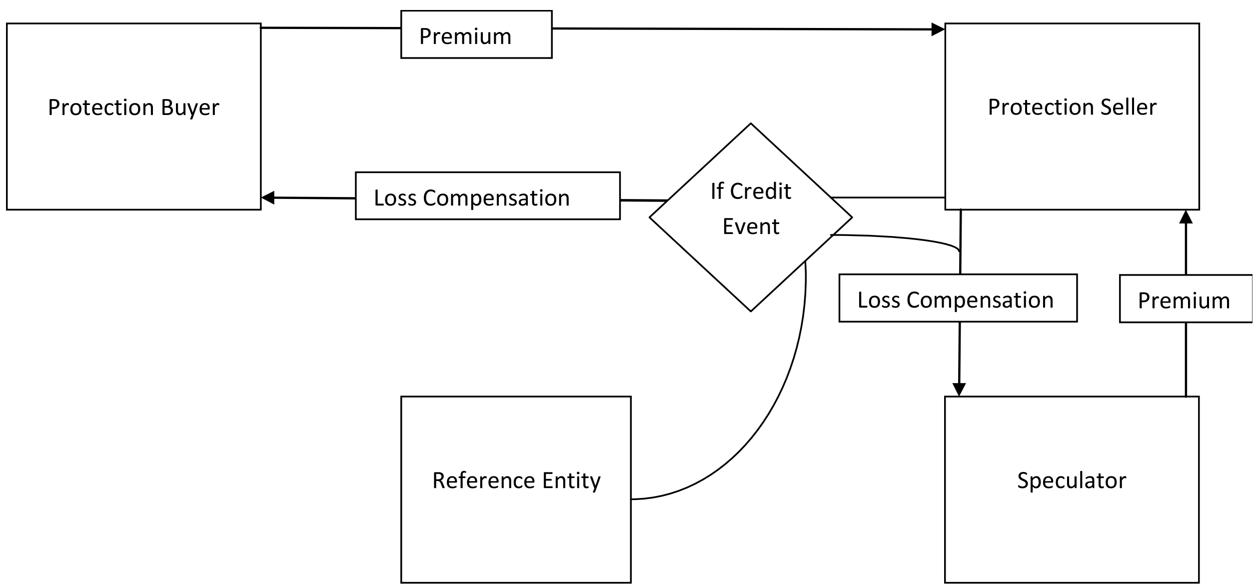
Via the credit default spread, it is possible to calculate the risk the market believes that the reference entity is facing. If the market believes that the reference entity is likely to repay its debt, the cost of guaranteeing that debt is going to be low. If the market believes there is a big risk that the reference entity will not be able to honour its obligations, the price for guaranteeing the debt is going to be higher.

Trading CDS

One important aspect of the CDS is how they are traded. Secondary markets exist for standardized contracts, but most CDS are traded over the counter. No one knows for certain how many CDS there are outstanding since the transactions usually are not registered on an exchange (enough CDS are, however, traded in standardized contracts to render a liquid price picture). One estimate of the total value of all outstanding CDS, is $ 38.6 trillion (ISDA, 2009). At the same time, the World Bank's latest statistically proven data, estimates the size of the world economy 2007 to $ 54.5 trillion.

CDS also give room for speculation. A fourth party, with no ties to the reference entity or the primary protection buyer, is often given the opportunity to buy the protection against credit risk as well, even if it faces no credit risk. A speculator might have reason to believe that the reference entity is about to get into financial distress and default on its debt. The speculator then goes to the protection seller and pays the credit default spread, which gives them the exact same conditions as the primary protection buyer. In case of a trigger event, the protection seller now has to give the loss compensation twice (figure 2).

Figure 2: **CDS and speculation**



Digital default swaps

A derivative closely related to CDS is digital default swaps, which, similarly to CDS, is an insurance against default. However, in contrast to CDS, it does not transfer default loss risk, but event risk, meaning that it gives a fixed payout should the reference entity default. This area is examined by Berd & Kapoor (2003) and can, because of the similarities between CDS and digital default swaps, be of interest for the reader of this thesis. The authors have not had access to digital default swaps market data.

3. THE CREDIT RATING PROCESS

To fully understand what is measured in the credit rating and in what ways the CDS resembles the credit ratings and in what ways they do not, it is of significant importance to go through the process of credit ratings. When a company wants to access debt markets, it often goes to a rating agency to get an objective view on its creditworthiness. The credit rating found plausible is then given to the company rated, who is also paying for the services. Also, some rating agencies publish the rating whether the purchasing company in the end desires so or not (Ekblom & Gusterman, 2009).

The credit rating and the cost of capital

The credit rating will largely affect the price the issuing company will have to pay in the debt markets. Since the credit rating is an assessment of the risk associated with the company, the higher risk the rating agency believes there is, the higher premium a lender will require to put money at work for the company. In other words, the rating agency has a great deal of power regarding the issuing company's financial costs. Still, many companies choose to stay as customers even though they might receive weak credit ratings, since a lack of a rating is often interpreted as far worse by debt markets than a bad rating.

The ratings given are not meant to be absolute but relative to other investments in the credit universe and do not indicate investment merit in absolute terms. Credit rating agencies are not involved in any transactions, thereby claiming independence that should be appreciated by both issuers and investors. That may not hold true, since the credit rating is crucial for most companies and many rating agencies have started advisory divisions, helping customers make the right moves to achieve a better credit rating and thus lower cost of capital.

Rating scale

This thesis uses Standard & Poor's rating scale, ranging from AAA (top) to D (defaulted) (appendix I). Everything above BBB- is considered to be investment grade, in contrast to everything below BBB-, which is considered to be non-investment grade (also known as speculative grade or junk). Speculative grade means that the issuer currently has the ability to honour its obligations but faces challenges such as a harshening business climate.

The credit rating market

The credit rating market is dominated by three players: Standard & Poor's, Moody's and Fitch's. There is some criticism regarding the way the credit rating market is functioning today. The US Securities and Exchange Commission is often held responsible for a lack of competitiveness, since its Nationally Recognized Statistical Rating Organization (NRSRO) gives companies regulatory easing, such as lower capital requirements, if given a good ratings from a rating agency on the NRSRO list (Per Lindvall, 2009). This excludes many smaller rating agencies from a big stake of the market. According to the Economist (2009-05-02), this situation is worsening with tighter control of the credit rating market, giving already dominant rating agencies further advantages. Also, a dominant position in the US gives a spillover effect to the rest of the world, due to size of the US economy.

The credit rating process

In assessing a company's creditworthiness, a rating agency starts by going through all public information available, such as annual reports and other financial data. Often, a dialogue with the management team of the company follows, where any questions can be sorted out and the management's view on the future can be taken into account. Then the rating agency goes back and reviews all assumptions behind the numbers in the public information and makes its own predictions about the company's financial position and the quality of its earnings. When this process is completed, a credit committee sits down and decides what rating to give. A rating should be consistent throughout the world and throughout industries, meaning that a AAA rating indicates the exact same ability to fulfil financial obligations. Credit ratings should also be consistent over cycles, meaning that it is not only the current condition of the company and the current business cycle that is taken into account, but also the expected future state of the business. Ideally, the credit rating should be persistent throughout business cycles.

Creditworthiness

There is a distinction in how the term creditworthiness is used in the industry. Standard & Poor's defines it as the risk that the debtor will default on any part of its loan, whereas Moody's takes the recovery value into account. To Standard & Poor's, it does not matter whether 99 percent of the financial obligation is repaid or not. Instead, it tries to measure the likeliness that any single lender will lose money, no matter the amount. Ceteris paribus, a company with three percent equity and no assets that can be recovered in case of default will get the same rating as a company with 99 percent equity tangible assets as covenant. In reality, a lender to the company with 99 percent equity runs a small risk to lose as much money as a lender to the first company, in case both companies go bankrupt.

4. PREVIOUS RESEARCH

There is naturally a widespread interest from, among others, lenders and investors of estimating the probability of default, why much research has been done in this field. However, this research is focused on accounting based models for estimating credit risk and default probabilities and the relationship between CDS data and default probabilities is relatively unexplored.

Older research targets multivariate credit-scoring models, which can be described as statistical analysis of financial ratios as a way of assigning a credit score to the examined company. Martin (1977) performs a study, similar to that of this thesis, where the failure of 58 US banks between 1970 and 1976 is analyzed using financial ratios with the objective of finding general characteristics indicating default. Findings indicate that only four of the 25 examined financial ratios are significantly correlated to default at the 5 percent level. Default is broadly defined as either bankruptcy, a merger with a second bank supervised by the government, or any other emergency measure to prevent imminent failure. It is also noted that the size of the sample is conservative, since the reasons for a merger are not always disclosed. Further research in the field of multivariate credit-scoring models is performed by West (1985), where the financial ratios of 1,900 US banks are scrutinized, with the objective of finding a model for assigning the banks a probability of being in distress. Indeed the thesis finds such a model to be promising in the evaluation of the condition of banks.

The multivariate credit-scoring models have been criticized for being too linear and not sufficiently dynamic in fast changing conditions (Altman & Saunders, 1998). With this criticism as background, a number of newer groups of models have evolved. One such group includes the option pricing models of Black and Scholes (1973) and Merton (1974). A second group of models are based on the Mortality Rate Concept presented by Altman (1989), which measure default risk on bonds using historical bond data.

As mentioned, the research in the field of estimating default probabilities using CDS spreads is limited. Notable exceptions include Hull et al (2004), which assesses the credit risk of companies using the option pricing model by Merton (1974), but with CDS spreads as input instead of balance sheet based measures. Further, JPMorgan (1999) has developed a model for estimating the underlying default probability of assets based on CDS spreads and recovery values. Linnergren-Fleck and Skarle (2008) applied this model on Swedish industrial companies for the period 2005 to 2008 and found that it renders higher default probabilities than those suggested by credit ratings as well as the probit model, an example of a multivariate credit-scoring model, outlined in Skogsvik (1987).

With the above as background this thesis intends to evaluate a relatively unexplored model for estimating credit risk and probability of default and compare this to the well established models of the credit rating companies.

5. HYPOTHESES

The statistical tests seek to test three things. Firstly, are CDS spreads better than credit ratings in predicting default (test one), secondly, are CDS spreads and credit ratings successful in assigning a higher probability of default for companies that subsequently reach default compared to the companies that survive (test two), and thirdly, do the credit rating institutions and the CDS market have similar views regarding the relative riskiness of financial companies (test three)?

Since this thesis makes a comparative study of the default probabilities as implied by credit ratings and CDS spreads, it is necessary to have two groups of companies, one with companies that has defaulted (group one) and one, a control group, with companies that are still going concerns (group two). This notation will be used henceforth.

It is important to point out that the probabilities of default implied by the credit ratings are not fully comparable to those as implied by the CDS spreads (Murgoci, 2009), why a direct comparison between the two probabilities is not possible. The reason for this difference is that the probabilities of default from credit ratings are actual outcomes and consequently risk free, whereas those from the CDS spreads are only estimated and thus carry an element of market risk. In practice this means that since the probability of default is unknown at the time of determining the CDS spread, a risk premium will be added to the spread to compensate for this element of uncertainty. Consequently, the probability of default given by the CDS spread will, ceteris paribus, be higher than the probability of default implied by the credit rating. For this reason, the statistical tests are, instead of making direct comparisons across groups, focused on comparing the probabilities of default for groups one and two for credit ratings and CDS spreads separately as well as comparing the average difference between groups one and two for credit ratings with the average difference between groups one and two for CDS spreads.

Test one

In test one, the difference between the average default probabilities for group one and group two, as implied by the credit ratings, is compared to the difference between the average default probabilities for the same two groups given by the CDS spreads. By doing so it can be evaluated whether there is a difference in how credit ratings or CDS spreads estimate probability of default in financial companies.

The alternative hypothesis is directional towards the difference being higher for CDS spreads (figure 3), since it is, in the light of the criticism aimed at credit rating institutions, interesting to test if the CDS market is indeed better in evaluating company risks.

Figure 3: **Hypothesis – test one**

$$H_0: \mu_D^{CDS\ spreads} = \mu_D^{Credit\ ratings}$$
$$H_1: \mu_D^{CDS\ spreads} > \mu_D^{Credit\ ratings}$$

$\mu_D^{CDS\ spreads} = the\ expected\ difference\ between\ group\ one\ and\ group\ two\ for\ CDS\ spreads$

$\mu_D^{Credit\ ratings} = the\ expected\ difference\ between\ group\ one\ and\ group\ two\ for\ credit\ ratings$

Test two

In test two, the average default probability for group one is compared to the average default probability for group two for credit ratings and CDS spreads separately. Test two is thus performed twice, once on credit rating data and once on CDS spread data. These two tests assess the ability of credit ratings and CDS spreads to assign a higher probability of default to the companies subsequent in default compared to the surviving companies.

As in test one, the alternative hypothesis is directional. Due to the growing complexity of financial companies it is interesting to evaluate the ability of the two institutions to distinguish “good” companies from “bad” (figure 4).

Figure 4: **Hypothesis – test two**

$$H_0: \mu_{PD}^1 = \mu_{PD}^2$$
$$H_1: \mu_{PD}^1 > \mu_{PD}^2$$

$\mu_{PD}^1 = the\ expected\ probability\ of\ default\ in\ group\ one\ for\ CDS\ spreads/credit\ ratings$

$\mu_{PD}^2 = the\ expected\ probability\ of\ default\ in\ group\ two\ for\ CDS\ spreads/credit\ ratings$

Test three

Test three seeks to evaluate whether credit ratings and CDS spreads differ in, or have the same, relative risk assessment of financial companies. To test this, the intergroup ranking of the default probabilities for all companies implied by the credit ratings is compared to the same intergroup ranking given by the CDS spreads, where the alternative hypothesis is two-sided meaning that the intergroup rankings are believed to be significantly different (figure 5).

Figure 5: **Hypothesis – test three**

$$H_0: ir^{CDS\ spreads} = ir^{Credit\ ratings}$$
$$H_1: ir^{CDS\ spreads} \neq ir^{Credit\ ratings}$$

$ir^{CDS\ spreads} = the\ internal\ ranking\ of\ probabilities\ of\ default\ for\ all\ companies\ for\ CDS\ spreads$

$ir^{Credit\ ratings} = the\ internal\ ranking\ of\ probabilities\ of\ default\ for\ all\ companies\ for\ credit\ ratings$

6. METHODOLOGY & DATA

Sample

The observed companies in this thesis have been chosen with assistance from Alexander Gusterman and Alexander Ekblom at Standard & Poor’s. As stated in the section above, it is, as this thesis makes a comparative study, necessary to have two groups of companies, one with companies that has defaulted (group one) and one, a control group, with companies that are still going concerns (group two). For both groups two sets of data are calculated, one from credit ratings and one from CDS spreads.

At the outset, all financial companies in the European and US markets have been potential objects of study. However, to fit the sample, two criteria have to be met. Firstly, the sample companies must fit a stated definition of default. As touched upon in the CDS description, there is not a general definition of default throughout the financial world. There are standardized contracts used in many secondary markets but also individualized contracts with specific definitions of default sold over the counter. In this thesis, default, and thus activation of the CDS contract, is defined as one or more of the following events occurring in the reference entity:

- Bankruptcy
- Failure to pay interest or principals when due to payment
- Government support needed for company to stay afloat

Other common CDS triggers have been assumed to play a minor role in the CDS spreads and their impact on the study to be negligible. The reason for including the first two trigger events is relatively straight forward. The third trigger event, on the other hand, requires an explanation as to why it is included. The underlying assumption is that private companies find government ownership undesirable and only turn to the government as a last resort. If the companies would not have been in severe financial distress, the market would have taken part in supporting the company rather than the government. Thereby, a government buying a stake in a privately held financial institution is seen as a way of avoiding an otherwise certain default. In addition to meeting this definition of default, the sample companies must have both a credit rating and an actively traded CDS. As a result of these two requirements, the sample has been limited to 20 in the group of defaulted companies and to 20 in the control group (appendix II). Consequently, availability, rather than randomization, has been guiding the selection of companies.

Period of study

The probabilities of default in this thesis extracted from credit rating and CDS data are from a specific date, which is here referred to as the date of measurement. Since the objective of this thesis is to compare the ability of credit ratings and CDS spreads to anticipate default in financial companies, it is necessary to set the date of measurement prior to the starting point of the current financial turmoil. With this in mind, the date of measurement is set to June 30, 2006, which is well before the date of the first default in the sample and prior to other irregularities in the financial market. The length of the measurement period is set to three years, thus ending on June 30, 2009, which is shortly after the date of publishing for this thesis. The reason for this irregularity is that the standard CDS contract used in this thesis has a term of three years and consequently expires on June 30, 2009. The companies included in group one have defaulted at different points during the period of study (appendix II).

Almost all credit ratings and CDS spreads used are from June 30, 2006. For a few companies, where data is not available on June 30, 2006, data from an adjacent date is used.

Probability of default – CDS spreads

The probability of default as implied by CDS spreads is not as accessible and intuitive as that from credit ratings. It is however rather simply derived from the CDS spread. This thesis will use the formula developed by JPMorgan (1998) for finding the probability of default (figure 6).

Figure 6: **Default probability from CDS spreads**

$$Probability\ of\ default = \sum_{t=1}^{T} \left[\frac{Quarterly\ CDS\ spread}{(1 - recovery\ value)}\right] / (1 + discount\ factor)^t$$

Following below is a derivation of the formula with a detailed explanation of its components.

Step one: CDS spread

As explained, the CDS spread is the annual price, measured as a percentage of the value protected, the protection seller charges for holding the protection buyer good in case the reference entity defaults. In the normal case, the CDS spread is divided into quarterly payments, but in this first step all payments are assumed to be paid on day one to initially avoid the added complexity of discounting.

Assuming that the protection buyer will lose the full investment in the reference entity in the event it defaults, the protection seller will have to make good the protection buyer the full value of the investment. With respect to this risk, the protection seller will charge a CDS spread equaling the probability of default, since the expected payout for the protection seller is in fact the probability of default (figure 7).

Figure 7: **Derivation of default probability from CDS spreads, step one**

$$Probability\ of\ default = CDS\ spread$$

Step two: Recovery value

In the normal case the protection buyer is able to recover some of the investment in the reference entity in the case of default. The amount recovered is referred to as the recovery value. In practice the recovery value is either the market price for which the investment in the reference entity can be sold post default or the part of the investment the lender receives from the reference entity in case of default. If, in the most extreme example, the recovery value is zero, the CDS spread will, as shown in step one above, be equal to the probability of default. However, if the assumed recovery value is positive, which is the normal case, the protection seller will demand a CDS spread, which is lower than the probability of default. This relationship appears as quite intuitive if keeping in mind that the obligation of the protection seller is to hold the protection buyer free from financial harm, meaning that the protection seller only has to make good the protection buyer the amount not recovered. The expected payout for the protection seller is consequently the probability of default multiplied by the recovery value, which is a percentage value between zero and 100 percent. Expecting a positive recovery value, the expected payout for the protection seller is consequently lower than the probability of default. Since the protection seller will demand a CDS spread equaling the expected payout, the CDS spread will also be lower than the probability of default.

Since the CDS spread is the probability of default adjusted for the recovery value, it is, in the derivation of the probability of default from the CDS spread, necessary to adjust for the recovery value taken into account when setting the CDS spread. This is done by dividing the CDS spread by [1 – recovery value] (figure 8).

Figure 8: **Derivation of default probability from CDS spreads, step two**

$$Probability\ of\ default = \frac{CDS\ spread}{(1 - recovery\ value)}$$

Step three: Discount factor

Additional complexity is added when considering that the annual CDS spread is divided into quarterly payments. The cash flows that the protection seller receives must consequently be discounted to day one, or the contract date.

The discount factor is the third and last component of the formula and combining all three components gives the full formula, where the sum of the discounted quarterly payments adjusted for recovery value equals the probability of default (figure 9).

Figure 9: **Derivation of default probability from CDS spreads, step three**

$$Probability\ of\ default = \sum_{t=1}^{T} \left[\frac{Quarterly\ CDS\ spread}{(1 - recovery\ value)}\right] / (1 + discount\ factor)^{t}$$

The formula in practice

With the concepts of recovery values, timing of cash flows, and the discount factor explained, the formula can be clarified further using two simple numerical examples.

Example 1: In this first example the following input is assumed:

$$CDS\ spread = 4.00\ \%$$

$$Quarterly\ CDS\ spread = 1.00\ \%$$

$$Recovery\ value = 50.00\ \%$$

$$Discount\ factor_{3\ month} = 4.00\ \%$$

This renders the following probability of default:

$$P^D = \sum_{t=1}^{T} \left[\frac{Quarterly\ CDS\ spread}{(1 - recovery\ value)}\right] / (1 + discount\ factor)^t$$

$$P^D = \sum_{t=1}^{4} \left[\frac{1.00\ \%}{(1 - 50.00\ \%)}\right] / (1 + 4.00\ \%)^t$$

$$P^D = 7.26\ \%$$

Table 1: **Probability of default from CDS spreads, example 1**

Quarter	1	2	3	4
CDS spread	1.00%	1.00%	1.00%	1.00%
Recovery value	50.00%	50.00%	50.00%	50.00%
Probability of default	2.00%	2.00%	2.00%	2.00%
Discount factor	4.00%	4.00%	4.00%	4.00%
Discounted value	1.92%	1.85%	1.78%	1.71%
Probability of default	*7.26%*			

Example 2: The second example assumes the following input values:

$$CDS\ spread = 4.00\ \%$$

$$Quarterly\ CDS\ spread = 1.00\ \%$$

$$Recovery\ value = 10.00\ \%$$

$$Discount\ factor_{3\ month} = 4.00\ \%$$

The probability of default thus becomes:

$$P^D = \sum_{t=1}^{T} \left[\frac{Quarterly\ CDS\ spread}{(1 - recovery\ value)}\right] / (1 + discount\ factor)^t$$

$$P^D = \sum_{t=1}^{4} \left[\frac{1.00\ \%}{(1 - 10.00\ \%)}\right] / (1 + 4.00\ \%)^t$$

$$P^D = 4.03\ \%$$

Table 2: **Probability of default from CDS spreads, example 2**

Quarter	1	2	3	4
CDS spread	1.00%	1.00%	1.00%	1.00%
Recovery value	10.00%	10.00%	10.00%	10.00%
Probability of default	1.11%	1.11%	1.11%	1.11%
Discount factor	4.00%	4.00%	4.00%	4.00%
Discounted value	1.07%	1.03%	0.99%	0.95%
Probability of default	*4.03%*			

Assumptions

To allow for the default probability to be calculated from the CDS spreads, it must be assumed that the CDS market is liquid. During the current financial turmoil the liquidity of CDS markets has, however, been adversely affected (Wall Street Journal, 2009), but since the CDS spreads used are from prior to the financial crisis, liquidity is assumed to not be an issue.

For simplicity, the quarterly CDS payments are assumed to be evenly distributed during the year, arising at the end of the third, sixth, ninth and twelfth month.

Probability of default – credit ratings

The credit ratings for the sample companies have been accessed through Standard & Poor's RatingsDirect, where the credit rating current on the measurement date of June 30, 2006 have been chosen.

This thesis uses long-term credit ratings, of which Standard & Poor's issues two types: one based on foreign obligations and one based on domestic obligations. For Western European and US companies in the private sector, there is normally no difference between these two ratings (Gusterman, 2009). Since all companies in the sample can be assumed to have significant exposure to international markets, the rating based on long-term foreign obligations is preferable to use. However, for a few companies in the sample, only the domestic rating is available why this rating is used instead. Due to the similarity of the two types of ratings for the companies in the sample, this is believed to not affect the accuracy of the study.

Data – CDS spreads

CDS spreads

CDS spreads used in this thesis have been accessed via Thomson Datastream. To avoid inaccuracies caused by large differences between the bid and offer rates, the mid value, have been used, which is the average of the bid and offer rates. The three year CDS spread for senior unsecured bonds is used for all companies, since it covers the entire period of study.

Recovery value

As for the recovery value the average value for defaulted financial institutions between 1971 and 1995 of 35.7 percent is used (Altman & Kishore, 1996). Important to note is that the actual recovery value can differ significantly between companies depending on factors such as the type of default and the amount of debt outstanding prior to the default (Moody's, 2004). In the default of Lehman Brothers, for example, the recovery rate was 9.3 percent for its senior unsecured bonds, whereas the corresponding value for Washington Mutual was 57.0 percent (Moody's, 2009). However, since the expected recovery value is what is taken into account when determining the CDS spread, using actual values for deriving the probability of default is faulty. The average recovery value found by Altman & Kishore (1996) is believed to correspond well to this expected recovery value.

Discount factor

As discount factor the running three month EURO LIBOR rate is used (table 3), where each quarterly payment is discounted by the corresponding LIBOR rate. For reasons of comparability, the EURO rate is used for all companies regardless of country of origin. Since the majority of companies are based in the EURO area and since the EURO is widely used internationally, this should not impair the accuracy of the study. Used rates have been accessed via the British Banker's Association (2009).

Table 3: **3 month EURO LIBOR rates**

	LIBOR 3 m - EUR
29/09/2006	3.42%
29/12/2006	3.72%
30/03/2007	3.93%
29/06/2007	4.17%

Data – credit ratings

The probability of default implied by credit ratings is derived from historical data of defaults by credit rating. This thesis uses statistics from Standard and Poor's (2009) of default rates between 1981 and 2008 (table 4). As described earlier, ratings by Standard & Poor's refer to the probability of default unadjusted for any possible recovery value, why it is thus not necessary to make adjustments for any such recovery value to allow for a comparison with the probability of defaults as implied by the CDS spreads.

For reasons of consistency with the CDS data, the default probability from credit ratings is measured over a three year period. For example, for a company rated A+ the default probability is 0.25 percent. Years 1-2 and 4-5 are included in table 4 for reference only.

***Table 4:* Global corporate cumulative average default rates by rating modifier, 1981 - 2008**

	Time horizon (years)				
Rating	**1**	**2**	**3**	**4**	**5**
AAA	0.00%	0.00%	0.09%	0.18%	0.27%
AA+	0.00%	0.06%	0.06%	0.13%	0.20%
AA	0.02%	0.04%	0.06%	0.17%	0.26%
AA-	0.04%	0.12%	0.25%	0.37%	0.49%
A+	0.06%	0.12%	0.28%	0.49%	0.66%
A	0.07%	0.19%	0.32%	0.47%	0.65%
A-	0.09%	0.27%	0.42%	0.61%	0.87%
BBB+	0.15%	0.47%	0.86%	1.20%	1.62%
BBB	0.26%	0.60%	0.89%	1.40%	1.94%
BBB-	0.34%	1.06%	1.92%	3.05%	4.09%
BB+	0.57%	1.48%	2.82%	4.11%	5.28%
BB	0.80%	2.48%	4.64%	6.56%	8.41%
BB-	1.38%	4.02%	6.76%	9.50%	11.85%
B+	2.56%	6.94%	11.13%	14.74%	17.44%
B	5.87%	11.97%	16.78%	20.04%	22.44%
B-	8.84%	16.57%	22.20%	26.08%	28.81%
CCC/C	25.67%	34.10%	39.25%	42.29%	44.93%

7. STATISTICAL TESTS

Test one

As stated previously, test one seeks to evaluate whether credit ratings and CDS spreads differ in their estimation of probability of default. The hypothesis in test one is tested using a one tailed Student's t-test with 18 degrees of freedom (sample size minus two) and a 5 percent level of significance (appendix III). This gives a listed t-value of 1.734. If the observed t-value is higher than the listed t-value, the null hypotheses can be rejected (figure 10).

Figure 10: **Student's t-test – test one**

$$t = \frac{\overline{D}^{CDS\ spreads} - \overline{D}^{Credit\ ratings}}{\sigma}$$

$\overline{D}^{CDS\ spreads} = the\ average\ difference\ between\ groups\ one\ and\ two\ for\ CDS\ spreads$

$\overline{D}^{Credit\ ratings} = the\ average\ difference\ between\ groups\ one\ and\ two\ for\ credit\ ratings$

$\sigma = the\ standard\ deviation\ of\ \overline{D}^{CDS\ spreads}\ and\ \overline{D}^{Credit\ ratings}$

Where σ is:

$$\sigma = \frac{\sigma^1}{n} + \frac{\sigma^2}{n}$$

$\sigma^1 = the\ standard\ deviation\ for\ the\ first\ set$

$\sigma^2 = the\ standard\ deviation\ for\ the\ second\ set$

In obtaining the standard deviation in test one, the difference in probabilities of default between group one and group two is measured for all companies individually. To allow for this, each company in group one is paired with a company in group two. Here, the alphabetical position of each company is deciding the pairing. The observant reader will note that the pairing of companies will have an effect on the resulting standard deviation. However, since the size of the sample reduces the effect any individual differences have on the total, the order of pairing is not likely to affect the end result.

Test two

Test two seeks to evaluate the ability of credit ratings and CDS spreads to assign a higher probability of default to the group of companies subsequent in default compared to the group of surviving companies. The hypothesis in test two is, as in test one, tested using a one tailed Student's t-test with 18 degrees of freedom (sample size minus two) and a 5 percent level of significance (appendix IV). Once again, this gives a listed t-value of 1.734 (figure 11).

Figure 11: **Student's t-test – test two**

$$t = \frac{\overline{D}^1 - \overline{D}^2}{\sigma}$$

$\overline{D}^1 = the\ average\ probability\ of\ default\ in\ group\ one\ for\ CDS\ spreads/credit\ ratings$
$\overline{D}^2 = the\ average\ probability\ of\ default\ in\ group\ two\ for\ CDS\ spreads/credit\ ratings$
$\sigma = the\ standard\ deviation\ of\ \overline{D}^1\ and\ \overline{D}^2$

Where σ is:

$$\sigma = \frac{\sigma^1}{n} + \frac{\sigma^2}{n}$$

$\sigma^1 = the\ standard\ deviation\ for\ group\ one$
$\sigma^2 = the\ standard\ deviation\ for\ group\ two$

Regarding both test one and two it is important to note, as stated in the Central Limit Theorem, that a sample size of at least 30 observations is recommended in order to reach reliable results using the Student's t-test. The authors are aware of this problem and the statistical weakness of results from a sample size of only 20 observations.

Test three

Test three seeks to determine whether credit ratings and CDS spreads give a similar relative measurement of risk for financial companies. This is done in two steps. In step one, the Spearman's rank correlation coefficient, ρ, is calculated. In the second step, the statistical significance of ρ is tested using the Student's t-test with 38 degrees of freedom (sample size minus 2) and a 5 percent level of significance (figure 12) (appendix V). The listed t-value in this case is 2.024.

Figure 12: **Spearman's rank correlation coefficient and Student's t-test – test three**

Calculation of ρ:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

$d_i = the\ sum\ of\ differences\ between\ the\ internal\ ranking\ of\ companies$

$n = the\ total\ number\ of\ companies\ in\ group\ one\ and\ group\ two$

Calculation of t:

$$t = \frac{\rho}{\sqrt{(1-\rho^2)/(n-2)}}$$

Since the sample size in this third test is 40, the recommended level for reaching reliable results of 30 observations is reached. Consequently, the criticism regarding test one and test two mentioned previously, does not apply to test three.

8. RESULTS

Test one

Test one gives an observed t-value of -0.083, which is lower than the listed t-value of 1.734 (table 5). Consequently, the null hypothesis cannot be rejected at the five percent level of significance, indicating that credit ratings and CDS spreads have been equal in their ability to predict default in financial companies.

Worth noting is that since the hypothesis is directional towards CDS spreads being the better indicator of financial distress, the negative observed t-value gives a weak indication that the direction of the alternative hypothesis should be the opposite. However, since the observed t-value is small in relation to the listed t-value, the difference would not have been statistically significant even if the hypothesis had been directional towards credit ratings being better at estimating probabilities of default.

Table 5: **Results – test one**

$D^{\text{CDS spreads}}$	0.001%
$D^{\text{credit ratings}}$	0.007%
σ	0.070%
T-value (obs)	-0.083
T-value, 18 df, 5 % sign.	1.734

Test two – CDS spreads

Test two (CDS spreads) gives an observed t-value of 0.018. Once again the observed value does not exceed the listed t-value of 1.734, indicating that the null hypotheses cannot be rejected at the five percent level of significance (table 6). CDS spreads have thus been unsuccessful in assigning a higher probability of default to the companies that subsequently have defaulted, compared to the companies in the surviving group.

Table 6: **Results – test two (CDS spreads)**

D^1	0.147%
D^2	0.146%
σ	0.041%
T-value (obs)	0.018
T-value, 18 df, 5 % sign.	1.734

Test two – credit ratings

Test two performed on the data for credit ratings renders an observed t-value of 0.124. Since this value is lower than the listed t-value of 1.734, the difference is once again not statistically significant (table 7). Hence, the null hypothesis cannot be rejected at the five percent level of significance, indicating that credit ratings, similarly to CDS spreads, have not been able to differentiate the surviving companies from the companies in default.

Table 7: **Results – test two (credit ratings)**

D^1	0.271%
D^2	0.265%
σ	0.052%
T-value (obs)	0.124
T-value, 18 df, 5 % sign.	1.734

Test three

The observed t-value from test three is 5.169, which exceeds the listed t-value of 2.024. Hence, the null hypothesis can be rejected at the five percent level of significance, meaning that the credit ratings and the CDS spreads have ranked the relative risk of the companies in group one and two differently.

Table 8: **Results – test three**

d^2	3810.5
ρ	0.643
T-value (obs)	5.169
T-value, 38 df, 5 % sign.	2.024

9. ANALYSIS & CONCLUSION

Even though the CDS market can reasonably be assumed to instantly react to new information, it is not proven to be better than the credit rating agencies in estimating probability of default. As discovered in test one, the credit ratings were actually slightly better, but the difference is not statistically significant. In conclusion, the CDS spreads were not more able than the credit ratings to predict default in financial companies.

Adding to the unsatisfying results for the two risk assessors is, as is clear in test two, that, neither of them was able to distinguish the companies subsequently in default from the companies that are still going concerns. It is, however, important to consider the effect of government support on this outcome. When the governments throughout the world showed their decisiveness to back up the financial system, it did not only help the financial institutions that got direct aid, but strengthened all financial companies by reducing systemic risk. It is possible that companies in the group of survivors would have defaulted, had not the trust in the financial sector recovered due to recent proof that the public sector would step in and help in case of distress. The fundamentals of the companies might not have differed, only at what time government aid was needed. However, this does not change the fact that half of the companies in the sample were given an overoptimistic risk assessment.

As for test three, the results can certainly be regarded as surprising. Considering how well renowned the rating agencies are, one can expect that credit ratings would have a larger influence on the risk estimation of the CDS market, but according to the results of test three, that does not seem to have been the case. Instead the credit rating agencies and the CDS market have differed wildly in the intergroup risk assessment of the companies in the sample. Consequently, investors have been able to choose between two risk assessors with different opinions, neither of them very successful.

10. DISCUSSION

It is difficult to find the definite underlying factors causing the poor estimation of probabilities of default in financial companies by the credit rating agencies as well as the CDS markets. However, it is still of interest to discuss a few of the issues that have been more debated than others.

Credit rating agencies have faced criticism for renouncing established requirements for reaching a certain credit rating, with the underlying aim of ensuring business retention. The end result of this practice, the criticism claims, is that higher credit ratings, and consequently lower probabilities of default, than merited have been given to financial companies. The credit rating agencies have also been accused of lacking objectivism in the setting of credit ratings as a consequence of having too close relationships with their clients. This criticism is mainly emerging from the credit rating agencies' practice of advising clients on how to reach a higher credit rating. However, also contributing to such close relationships is certainly the lack of competitiveness in the industry where a few large players own close to the entire market.

The CDS market has, for example, met critique due to the practice of over the counter trading, making an overview of the market difficult and transparency of prices clouded. In spite of this, the CDS market has been sufficiently liquid to provide correct spreads and thus an accurate picture of the market's estimation of the probability of default. Consequently, the ability of the CDS market to evaluate the probability of default in financial companies, in comparison to that of the credit rating agencies, ought to be a good measure of the credibility of the criticism directed at the credit rating agencies, since the CDS market must be considered to be free from the biasing factors the credit rating agencies are said facing. As found in this thesis, the CDS market does indeed provide an alternative view on the risk of financial companies. However, this alternative view is equally poor as the one given by the credit rating agencies, indicating that the criticism aimed at the credit rating agencies has little credibility for the period of study. This fact does not weaken the argument that a change in the credit rating industry might be needed, but it provides proof that the primary explanation to the inaccuracies in risk assessment lies elsewhere. A probable such explanation to the poor estimation of risk, is that the financial companies have grown too complex to allow for both credit rating agencies as well as the CDS market to make correct evaluations of their true probability of default. It is not within the scope of this thesis to address the question of how to solve this problem of complexity, or alternatively how to improve risk measurement models to cope with increased complexity. It is, however, in the light of the current economic crisis, clear that it is of outmost importance that the ability of both credit rating agencies and the CDS market to correctly assess risk is greatly improved.

As an ending remark, it is interesting to discuss the value of extrapolating on the results found in this thesis. The period of study is June 30, 2006 to June 30, 2009. Even though the period is characterised of financial turmoil, the authors believe that these results say more about the risk assessors' abilities in general, than just for this specific period. None or very few of the stakeholders in the financial markets were able to predict what was to happen, but risk assessment is not only for sunny days. It is for days of distress they are truly needed.

Suggestions for further research

As mentioned, a limitation of this thesis is the small number of companies in the sample, with the number of companies in default as the restrictive factor. With time it is probable that more financial institutions will default making a replicating study, performed when the effects of the current crisis are clear, highly interesting. Also, it is naturally so that the models presented in this thesis are not limited to financial institutions. It is therefore possible to perform a similar study on sectors in addition to the financial.

Further, in order to make pricing more transparent, discussions are in progress to form an international clearinghouse for CDS trading. The effects on CDS spreads of creating such an institution are naturally not clear, but performing a replicating study when a clearinghouse is in place is highly interesting.

Lastly, as the credit ratings provided by Standard & Poor's imply a probability of default that excludes any recovery value, they correspond better to digital default swaps, than CDS, as the former do not take into account the recovery value in its pricing should default occur. The probability of default given by CDS, which take into account an expected recovery value when priced, are more easily compared to the credit ratings by Moody's, as they imply a probability of default including any recovery value. Hence, by comparing the credit ratings of Standard & Poor's to digital default swaps and the credit ratings of Moody's to CDS, one can avoid the problem of having to assume a recovery value. The reason for not doing such a comparison in this thesis is limited access to data.

Disclaimer

Several underlying assumptions and methodological choices in this thesis can be questioned.

Firstly, the sample of financial companies is not sufficiently large to assume a normal distribution, which is required to achieve statistical significance using a Student's t-test. According to the Central Limit Theorem, a minimum of 30 observations is needed to assume a normal distribution, which should be compared to the 20 observations used in this thesis.

Secondly, the sample of defaulted financial companies is not randomized but availability has been the criteria. The surviving companies are the financial companies first recalled by the authors that have both an active credit rating and a liquid CDS market. The defaulted companies are suggested by Alexander Gusterman and Alexander Ekblom of Standard & Poor's, who claim that the sample is close to the entire population.

Thirdly, the recovery value used is the mean for financial companies from 1971 to 1995 and is not updated to present time. That number is, however, also used by practitioners why it reflects the expectations of the market, which is what the authors set out to assess.

Lastly, the three year CDS contracts used in this thesis have not yet expired. There is a possibility that companies now in the group of surviving companies may run into financial distress between May 2009, when these words are written, and June 2009 when the contracts expire. In that case, the results in this thesis might be skewed.

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12. APPENDIX I

STANDARD & POOR'S RATING SCALE

	Rating	Indication
	AAA	Extremely strong capacity to meet financial commitments. Highest rating
	AA	Very strong capacity to meet financial commitments
	A	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions
	BBB	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions
Investment Grade	BBB-	Considered lowest investment grade by market participants
Speculative Grade	BB+	Considered highest speculative grade by market participants
	BB	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions
	B	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments
	CCC	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments
	CC	Currently highly vulnerable
	C	A bankruptcy petition has been filed or similar action taken, but payments of financial commitments are continued
	D	Payment default on financial commitments

13. APPENDIX II

SAMPLE

Group 1: Default	Country	Type of default	Date of default	Group 2: Survivors	Country
American International Group	US	Government support	September 16, 2008	Allianz	Germany
Bayern LB	Germany	Government support	October 21, 2008	American Express	US
Bear Stearns	US	Bankruptcy	March 14, 2008	Banco Santander	Spain
Citi Group	US	Government support	November 26, 2008	Bank of America	US
Commerzbank	Germany	Government support	January 9, 2009	Bank of New York Mellon	US
Dexia	Belgium	Government support	September 30, 2008	Barclays Bank	UK
Fannie Mae	US	Government support	September 7, 2008	BNP Paribas	France
Fortis	Netherlands	Government support	September 28, 2008	Credit Agricole	France
Freddie Mac	US	Government support	September 7, 2008	Credit Lyonnais	France
HBOS	UK	Government support	October 13, 2008	Danske Bank	Denmark
HSH Nordbank	Germany	Government support	February 24, 2009	Deutsche Bank	Germany
Hypo Real Estate Bank	Germany	Government support	September 29, 2008	Goldman Sachs	US
LBBW	Germany	Government support	November 21, 2008	HSBC Bank	UK
Lehman Brothers	US	Bankruptcy	September 15, 2008	ING Groep	Netherlands
Lloyds TSB Bank	UK	Government support	October 13, 2008	JP Morgan Chase	US
Northern Rock	UK	Government support	February 22, 2008	Munich Re	Germany
Royal Bank of Scotland	UK	Government support	October 13, 2008	Nationwide Building Society	UK
UBS	Switzerland	Government support	October 17, 2008	Nordea Bank Sweden	Sweden
Wachovia	US	Government support*	October 4, 2008	Societe Generale	France
Washington Mutual	US	Bankruptcy	September 25, 2008	Swedbank	Sweden

* Wachovia w as taken over by Wells Fargo in 2008 in a deal brokered by the FDIC

14. APPENDIX III

TEST 1

Credit ratings

Group 1: Default	PD1	Group 2: Survivors	PD2	D(CR)
American International Group	0.060%	Allianz	0.860%	-0.800%
Bayern LB	0.320%	American Express	0.280%	0.040%
Bear Stearns	0.320%	Banco Santander	0.250%	0.070%
Citi Group	0.250%	Bank of America	0.250%	0.000%
Commerzbank	0.420%	Bank of New York Mellon	0.280%	0.140%
Dexia	0.060%	Barclays Bank	0.060%	0.000%
Fannie Mae	0.250%	BNP Paribas	0.060%	0.190%
Fortis	0.280%	Credit Agricole	0.250%	0.030%
Freddie Mac	0.250%	Credit Lyonnais	0.250%	0.000%
HBOS	0.250%	Danske Bank	0.250%	0.000%
HSH Nordbank	0.320%	Deutsche Bank	0.250%	0.070%
Hypo Real Estate Bank	0.860%	Goldman Sachs	0.280%	0.580%
LBBW	0.280%	HSBC Bank	0.060%	0.220%
Lehman Brothers	0.250%	ING Groep	0.250%	0.000%
Lloyds TSB Bank	0.060%	JP Morgan Chase	0.280%	-0.220%
Northern Rock	0.280%	Munich Re	0.280%	0.000%
Royal Bank of Scotland	0.250%	Nationwide Building Society	0.280%	-0.030%
UBS	0.060%	Nordea Bank Sweden	0.250%	-0.190%
Wachovia	0.280%	Societe Generale	0.250%	0.030%
Washington Mutual	0.320%	Swedbank	0.320%	0.000%
Average				0.007%
Variance				0.001%
Variance, D(CR) & D(CDS)				0.000%
Standard deviation, D(CR) & D(CDS)				0.070%
T-value (observed)				-0.083

CDS

Group 1: Default	PD1	Group 2: Survivors	PD2	D(CDS)
American International Group	0.134%	Allianz	0.120%	0.014%
Bayern LB	0.147%	American Express	0.170%	-0.022%
Bear Stearns	0.226%	Banco Santander	0.103%	0.123%
Citi Group	0.099%	Bank of America	0.116%	-0.017%
Commerzbank	0.160%	Bank of New York Mellon	0.129%	0.031%
Dexia	0.148%	Barclays Bank	0.081%	0.068%
Fannie Mae	0.057%	BNP Paribas	0.054%	0.003%
Fortis	0.163%	Credit Agricole	0.071%	0.092%
Freddie Mac	0.057%	Credit Lyonnais	0.044%	0.013%
HBOS	0.069%	Danske Bank	0.031%	0.038%
HSH Nordbank	0.129%	Deutsche Bank	0.120%	0.009%
Hypo Real Estate Bank	0.116%	Goldman Sachs	0.226%	-0.110%
LBBW	0.213%	HSBC Bank	0.072%	0.141%
Lehman Brothers	0.310%	ING Groep	0.085%	0.225%
Lloyds TSB Bank	0.051%	JP Morgan Chase	0.156%	-0.105%
Northern Rock	0.382%	Munich Re	0.141%	0.240%
Royal Bank of Scotland	0.068%	Nationwide Building Society	0.760%	-0.692%
UBS	0.040%	Nordea Bank Sweden	0.076%	-0.036%
Wachovia	0.113%	Societe Generale	0.057%	0.057%
Washington Mutual	0.254%	Swedbank	0.310%	-0.055%
				0.001%
				0.000%

15. APPENDIX IV

TEST 2

Credit ratings					CDS				
Group 1: Default	**PD1**	**Group 2: Survivors**	**PD2**	**D(CR)**	**Group 1: Default**	**PD1**	**Group 2: Survivors**	**PD2**	**D(CDS)**
American International Group	0.060%	Allianz	0.860%	-0.800%	American International Group	0.134%	Allianz	0.120%	0.014%
Bayern LB	0.320%	American Express	0.280%	0.040%	Bayern LB	0.147%	American Express	0.170%	-0.022%
Bear Stearns	0.320%	Banco Santander	0.250%	0.070%	Bear Stearns	0.226%	Banco Santander	0.103%	0.123%
Citi Group	0.250%	Bank of America	0.250%	0.000%	Citi Group	0.099%	Bank of America	0.116%	-0.017%
Commerzbank	0.420%	Bank of New York Mellon	0.280%	0.140%	Commerzbank	0.160%	Bank of New York Mellon	0.129%	0.031%
Dexia	0.060%	Barclays Bank	0.060%	0.000%	Dexia	0.148%	Barclays Bank	0.081%	0.068%
Fannie Mae	0.250%	BNP Paribas	0.060%	0.190%	Fannie Mae	0.057%	BNP Paribas	0.054%	0.003%
Fortis	0.280%	Credit Agricole	0.250%	0.030%	Fortis	0.163%	Credit Agricole	0.071%	0.092%
Freddie Mac	0.250%	Credit Lyonnais	0.250%	0.000%	Freddie Mac	0.057%	Credit Lyonnais	0.044%	0.013%
HBOS	0.250%	Danske Bank	0.250%	0.000%	HBOS	0.069%	Danske Bank	0.031%	0.038%
HSH Nordbank	0.320%	Deutsche Bank	0.250%	0.070%	HSH Nordbank	0.129%	Deutsche Bank	0.120%	0.009%
Hypo Real Estate Bank	0.860%	Goldman Sachs	0.280%	0.580%	Hypo Real Estate Bank	0.116%	Goldman Sachs	0.226%	-0.110%
LBBW	0.280%	HSBC Bank	0.060%	0.220%	LBBW	0.213%	HSBC Bank	0.072%	0.141%
Lehman Brothers	0.250%	ING Groep	0.250%	0.000%	Lehman Brothers	0.310%	ING Groep	0.085%	0.225%
Lloyds TSB Bank	0.060%	JP Morgan Chase	0.280%	-0.220%	Lloyds TSB Bank	0.051%	JP Morgan Chase	0.156%	-0.105%
Northern Rock	0.280%	Munich Re	0.280%	0.000%	Northern Rock	0.382%	Munich Re	0.141%	0.240%
Royal Bank of Scotland	0.250%	Nationwide Building Society	0.280%	-0.030%	Royal Bank of Scotland	0.068%	Nationwide Building Society	0.760%	-0.692%
UBS	0.060%	Nordea Bank Sweden	0.250%	-0.190%	UBS	0.040%	Nordea Bank Sweden	0.076%	-0.036%
Wachovia	0.280%	Societe Generale	0.250%	0.030%	Wachovia	0.113%	Societe Generale	0.057%	0.057%
Washington Mutual	0.320%	Swedbank	0.320%	0.000%	Washington Mutual	0.254%	Swedbank	0.310%	-0.055%
Average	0.271%		0.265%		**Average**	0.147%		0.146%	
Variance	0.000%		0.000%		**Variance**	0.000%		0.000%	
Variance, PD1 & PD2			0.000%		**Variance, PD1 & PD2**			0.000%	
Standard deviation, PD1 & PD2			0.052%		**Standard deviation, PD1 & PD2**			0.041%	
T-value (observed)			0.124		**T-value (observed)**			0.018	

16. APPENDIX V

TEST 3

Credit ratings	PD(CR)	Rank	CDS	PD(CDS)	Rank	Diff	$Diff^2$
Allianz	0.860%	1.5	Allianz	0.120%	19.5	-18.0	324.0
American Express	0.280%	13.5	American Express	0.170%	9.0	4.5	20.3
American International Group	0.060%	34.0	American International Group	0.134%	16.0	18.0	324.0
Banco Santander	0.250%	26.0	Banco Santander	0.103%	24.0	2.0	4.0
Bank of America	0.250%	26.0	Bank of America	0.116%	21.5	4.5	20.3
Bank of New York Mellon	0.280%	13.5	Bank of New York Mellon	0.129%	17.0	-3.5	12.3
Barclays Bank	0.060%	37.5	Barclays Bank	0.081%	27.0	10.5	110.3
Bayern LB	0.320%	6.0	Bayern LB	0.147%	14.0	-8.0	64.0
Bear Stearns	0.320%	6.0	Bear Stearns	0.226%	6.5	-0.5	0.3
BNP Paribas	0.060%	37.5	BNP Paribas	0.054%	36.0	1.5	2.3
Citi Group	0.250%	26.0	Citi Group	0.099%	30.0	-4.0	16.0
Commerzbank	0.420%	26.0	Commerzbank	0.160%	25.0	1.0	1.0
Credit Agricole	0.250%	3.0	Credit Agricole	0.071%	11.0	-8.0	64.0
Credit Lyonnais	0.250%	26.0	Credit Lyonnais	0.044%	38.0	-12.0	144.0
Danske Bank	0.250%	26.0	Danske Bank	0.031%	40.0	-14.0	196.0
Deutsche Bank	0.250%	26.0	Deutsche Bank	0.120%	19.5	6.5	42.3
Dexia	0.060%	37.5	Dexia	0.148%	13.0	24.5	600.3
Fannie Mae	0.250%	26.0	Fannie Mae	0.057%	33.5	-7.5	56.3
Fortis	0.280%	13.5	Fortis	0.163%	10.0	3.5	12.3
Freddie Mac	0.250%	26.0	Freddie Mac	0.057%	33.5	-7.5	56.3
Goldman Sachs	0.280%	13.5	Goldman Sachs	0.226%	6.5	7.0	49.0
HBOS	0.250%	26.0	HBOS	0.069%	31.0	-5.0	25.0
HSBC Bank	0.060%	37.5	HSBC Bank	0.072%	29.0	8.5	72.3
HSH Nordbank	0.320%	6.0	HSH Nordbank	0.129%	18.0	-12.0	144.0
Hypo Real Estate Bank	0.860%	1.5	Hypo Real Estate Bank	0.116%	21.5	-20.0	400.0
ING Groep	0.250%	26.0	ING Groep	0.085%	26.0	0.0	0.0
JP Morgan Chase	0.280%	13.5	JP Morgan Chase	0.156%	12.0	1.5	2.3
LBBW	0.280%	13.5	LBBW	0.213%	8.0	5.5	30.3
Lehman Brothers	0.250%	26.0	Lehman Brothers	0.310%	3.5	22.5	506.3
Lloyds TSB Bank	0.060%	37.5	Lloyds TSB Bank	0.051%	37.0	0.5	0.3
Munich Re	0.280%	13.5	Munich Re	0.141%	15.0	-1.5	2.3
Nationwide Building Society	0.280%	13.5	Nationwide Building Society	0.760%	1.0	12.5	156.3
Nordea Bank Sweden	0.250%	26.0	Nordea Bank Sweden	0.076%	28.0	-2.0	4.0
Northern Rock	0.280%	13.5	Northern Rock	0.382%	2.0	11.5	132.3
Royal Bank of Scotland	0.250%	26.0	Royal Bank of Scotland	0.068%	32.0	-6.0	36.0
Societe Generale	0.250%	26.0	Societe Generale	0.057%	35.0	-9.0	81.0
Swedbank	0.320%	6.0	Swedbank	0.310%	3.5	2.5	6.3
UBS	0.060%	37.5	UBS	0.040%	39.0	-1.5	2.3
Wachovia	0.280%	13.5	Wachovia	0.113%	23.0	-9.5	90.3
Washington Mutual	0.320%	6.0	Washington Mutual	0.254%	5.0	1.0	1.0
Sum of $Diff^2$							3810.5
Rho							0.643
T-value (observed)							5.169