STOCKHOLM SCHOOL OF ECONOMICS
DEPARTMENT OF ACCOUNTING
MASTER THESIS IN ACCOUNTING AND FINANCIAL MANAGEMENT

Default Probabilities

Three Different Models of Estimating Default Probabilities

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ABSTRACT: The aim of this study is to examine three different ways of estimating the probability of default; one based on historical accounting data, as by Skogsvik 1987, one based on the implied probabilities from credit ratings and one model that estimates the implied probability of default from the pricing of 1 year Credit Default Swaps (CDS). The sample consists of 15 large Swedish companies with traded CDSs over the time period of January 1, 2005 to March 31, 2008. The conclusion reached is that the large increase of the probability of default as suggested by the increase in CDS spreads is not supported by the other models. Several possible explanations for this are identified and discussed. The second conclusion is that the Rating agencies and Probit Model both show much more stable results for the entire period, on significantly lower and more reasonable levels then the CDS Model. Thirdly one could state that as none of the companies in the sample have defaulted the Probit Model offers the best default indication.

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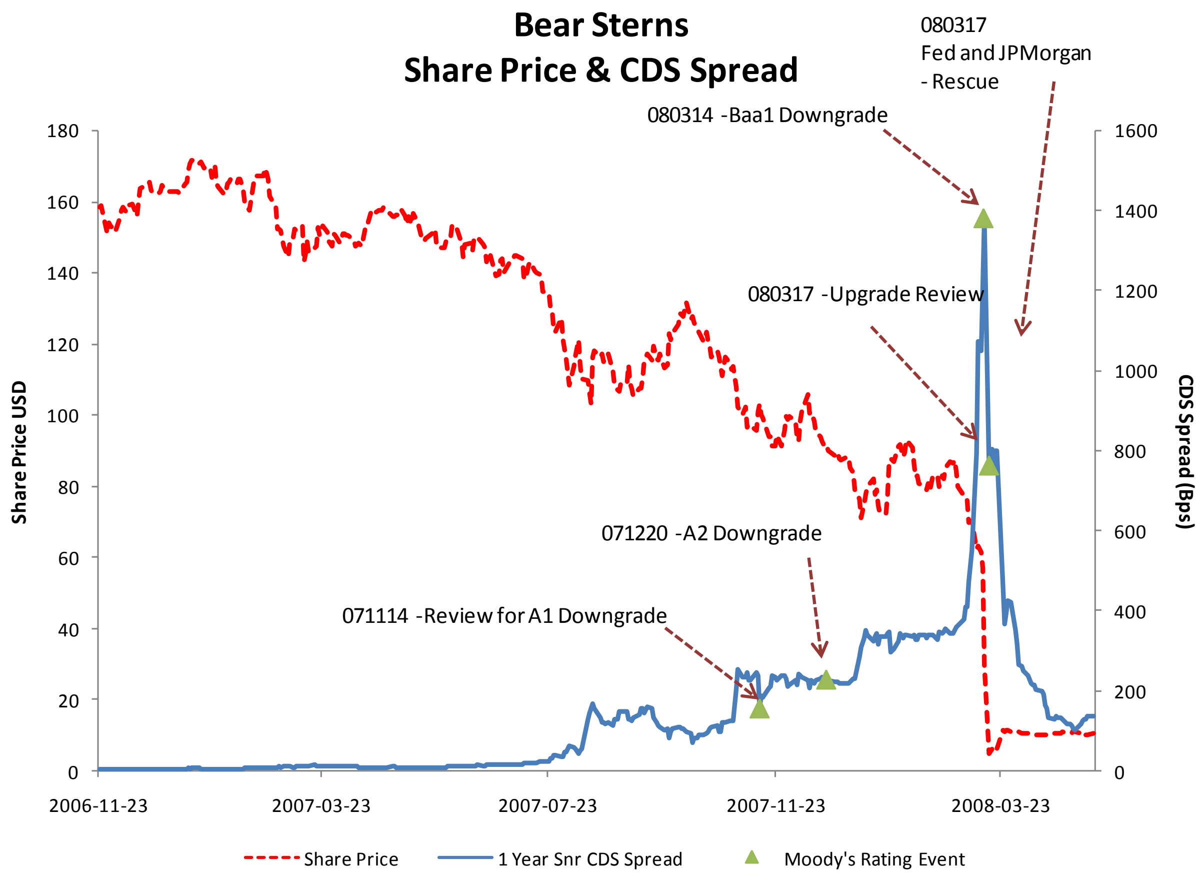

An illustrative example of how default risks influences a company, its share price and the CDS spread is that of the American investment bank ***Bear Sterns****. In the summer of 2007, the emerging credit crisis caused the market's view on Bear Sterns probability of default to increase dramatically, and on March 17, 2008 the US Federal Reserve rescued the bank from bankruptcy. In the month prior to the rescue the Bear Sterns share price plunged and the CDS spread skyrocketed with over 1000 bps.*

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1. Introduction

The importance of being able to estimate business failure is essential in various business decisions. The probability of failure influences the decision making process when determining the terms of a loan, investing in shares or when signing large agreements with suppliers or customers. For many companies in the financial sector, new regulations have increased the importance of accurate and reliable measurement of probabilities of failure in order to estimate their risk exposure.

One of the most illustrative examples of the importance of probability of failure is when valuing a bond. If the probability of failure is assumed to be constant for all periods, the value of a bond is given by the formula:

$$Value\ of\ Bond = \sum_{t=1}^{T} \frac{(1-P_{fail})^t \cdot C}{(1+r)^t} + \frac{(1-P_{fail})^T \cdot F}{(1+r)^T}$$

Where

$P_{fail} = Probability\ of\ failure$

$C = Coupon$

$r = discount\ rate$

$F = Face\ value$

When a bond with a face value of 100 currency units and a yearly coupon of 10 is valued using a discount rate of 10%, the present value is 100 if there is no risk for default regardless the duration of the bond. If the probability of default is taken into account, the value of the bond is affected, as seen in table 1. The difference can be large, for example a 10 year bond with a probability of default of 5% is worth 28% less than a corresponding risk-free bond. Hence, the probability of default is highly important to take into account, and it is crucial to estimate the probability as correct as possible.

Loan PV Calculation							
		Default Probability					
		0,00%	0,10%	1,00%	5,00%	10,00%	50,00%
Year	1	100,0	99,9	99,0	95,0	90,0	50,0
	5	100,0	99,6	95,9	81,0	65,2	10,1
	10	100,0	99,3	93,5	71,8	52,4	8,4
	15	100,0	99,2	92,1	67,4	47,7	8,3
Face Value		100,0					
Discount rate		10%					
Coupon		10					

Table 1: The probability of failure and the effect on the net present value of a bond.

The traditional way of estimating default probabilities is to use credit ratings from well-respected credit rating agencies. Using these ratings is however not as straightforward as many investors have believed. This became evident during the recent credit crisis in the financial markets, where several financial instruments with the highest credit ratings lost a large portion of their value in only a few weeks. The rating agencies were widely criticized for having given these instruments such high ratings, since investors presumed that instruments with high credit ratings implied low-risk investments. The rating agencies defended themselves by stating that they only rated the credit risk; that is the risk the rated instrument or entity will not be able to meet its financial obligations. However they do not rate the liquidity risk. In relation to the credit crisis rating agencies have also been criticized for being too slow to update their ratings and critics have also pointed at the agency problem arising from the contractual agreement between the rating agency and the rated company. The reason for this criticism is the fact that it is the rated company that pays the rating agency for the ratings.

Hence, there is a demand for alternative ways of estimating default probabilities. One alternative is to use statistical models that discover connections between the probability of default and different accounting measures, by identifying certain accounting ratios that are connected to survival or default of companies. Among the benefits are that they are free from subjective opinions, since they only rely on historical accounting data when estimating the default probabilities. As a consequence, such models are impossible to influence by rating agencies, and because they only rely on publicly available data they are also cost efficient. Among the drawbacks are that it is not always plausible to build estimations about future business failure on past performance. However, these models have proven to be very stable over time and give default probabilities with a one year accuracy of 83.3% or in other words being able get the type II error down to 16.7% (Skogsvik, 1987).

Another new exiting opportunity has risen through the emergence of the credit derivative market. It is today possible to buy a derivative that separates the credit risk from a bond, and trade solely the risk of the underlying asset. These instruments, called Credit Default Swaps, can be traded and thus it is possible to obtain a continuously updated market price on the credit risk of a company. By studying the prices of such instruments, the implicit probability of failure that the market puts on an entity can be estimated.

In light of the importance of measuring the probability of default accurately, it is interesting to examine if there are any distinct differences between the methods when looking at as sample of Swedish companies.

1.1 Purpose

The purpose of this thesis is to compare different ways of estimating the probability of default. This thesis will study three different models; one model that uses historical accounting data, the **Probit Model** as developed by Skogsvik (Skogsvik 1987), one model which uses implied probabilities from **rating agencies** and one model that estimate the implied probability of default derived from the pricing of one year **CDS Instruments**.

The main issues that will be discussed and analyzed in regard to the purpose are the following:

1. *What are the implied general levels of default probabilities in large Swedish companies between 2005 – 2008 for the different models?*

2. Are *there any general trends in the average and median default probability and do these trends differ according to the models used?*

1.2 Delimitations

Company Selection Table			
Company	CDS Spreads Available	Probit Model Applicable	Included in Sample
ABB	✓	✓	✓
Atlas Copco	✓	✓	✓
Electrolux	✓	✓	✓
Ericsson	✓	✓	✓
Sandvik	✓	✓	✓
SAS	✓	✓	✓
SCA	✓	✓	✓
Scania	✓	✓	✓
Securitas	✓	✓	✓
SKF	✓	✓	✓
Stora Enso	✓	✓	✓
Swedish Match	✓	✓	✓
Telia Sonera	✓	✓	✓
Volvo	✓	✓	✓
Vattenfall	✓	✓	✓
Assa Abloy	✗	✓	✗
Birka Energi	✗	✓	✗
Holmen	✗	✓	✗
Stena	✗	✓	✗
IF	✗	✗	✗
Investor	✓	✗	✗
Nordea	✓	✗	✗
SEB	✓	✗	✗
Skandia	✓	✗	✗
Swedbank	✓	✗	✗

Table 2: List of companies included in the sample. First, all companies with traded CDSs are included, then some are excluded due to either lack of CDS data for the whole period, or due to the fact that the Probit Model is not applicable.

This is a survey made on Swedish companies; hence only Swedish companies are included in the sample. The Probit Model as developed by Skogsvik (Skogsvik 1987) was based on data from Swedish manufacturing companies. However, a study made by Lundén and Rimbäck (Lundén and Rimbäck 2003) proved that Skogsvik's model also worked fairly well on other types of companies, hence companies from other industries are included with the exception of banks, insurance and investment companies. The reason for excluding these firms is that the accounting measures used in Skogsvik's model do not apply for financial.

One major factor that have excluded many companies from the sample is the availability of CDS spreads: since the study uses the prices of CDS contracts, the CDS spreads, to calculate the implied default probability it has been a condition for companies being included in the sample that there must be available data of CDS spreads for the entire period between January 2005 and January 2008. The reason for choosing this period is that there are only a few available CDS spreads from Datastream earlier than 2005.

A final condition has been that Moody's or Standard & Poor's (S&P), the two most well-known rating agencies as well as the agencies with the largest presence in Sweden, must have published ratings for the companies for the entire period. In Table 2 a list of the companies included in the survey is provided.

2. Theoretical Framework

2.1 Probit Model

One way of predicting business failure is to rely on historical accounting data. Skogsvik (Skogsvik 1987) chose probit analysis for the estimation between accounting ratios and business failure. By using probit analysis, the value of an index variable *V* can be calculated and the variable can be assumed to be normally distributed enabling the probability of default to be expressed in percent. Earlier studies, such as Altman (Altman, 1968), produced a value that was only informative when put in relation to another value (comparing if firm 1 is more likely to default than firm 2), but it did not provide any information about the absolute probability of failure for an entity.

Skogsvik's sample consisted of 379 Swedish companies, 51 failure companies and 328 non-failure companies. All companies belonged to the sectors "Mining and Quarrying" or "Manufacturing Industry". All companies were limited liability companies with more than 200 employees or more then 20 MSEK in assets in 1970 prices during any of the years 1966-1971. The empirical data refers to the period 1966-1980. The definition of a failure in Skogsvik's model was bankruptcy or composition arrangement, voluntary shut-down or the case where any kind of government support was provided.

Probit analysis was used in order to test the joint predictive ability of various groups of financial ratios. The result from Skogsvik's research was a linear function where different financial ratios were weighted in order to obtain the best possible accuracy. Skogsvik tried different combinations of 17 representative traditional ratios and some normalized versions of these ratios. The most accurate results were obtained, with a prediction span of one year, with five normal ratios and one normalized ratio. The mean percentage error was then 16.7%, meaning that approximately one out of six companies was expected to be classified incorrectly.

The model Skogsvik created is stated as follows:

$$\mathbf{V = -1.5 - 4.3 \cdot R_1 + 22.6 \cdot R_2 + 1.6 \cdot R_3 - 4.5 \cdot R_4 + 0.2 \cdot R_5 - 0.1 \cdot R_6.}$$

The ratios labeled R_X, that gave the best predictions, were traditional measures of profit and solidity:

R_1: Return on assets, defined as EBIT divided by average total assets. This ratio is a traditional measure of the profitability of the company's assets.

R_2: Interest rate, defined as interest expense divided by average liabilities. This gives an indication of how the creditors value the risk in the company: the higher interest rate, the higher risk premium is added by the institutions that lend out money.

R_3: Inverted inventory turnover, defined as average inventory divided by sales.

R_4: Shareholder equity ratio, defined as owner's equity divided by total assets, a ratio that measures the solidity of the company.

R_5: Change in owner's equity, defined as the growth in owner's equity (positive or negative) divided by opening book value of owner's equity.

R_6: A normalized measure of R_2, where the interest rate during the last four years period is taken into account.

(see Appendix 2 for a more explanatory definition)

The sample of companies used included 51 failure companies out of 379; equal to a failure ratio of more than 13%, which is higher than the actual probability of failure in the grand population. This causes a "choice-based sample bias"; the number of failure companies in the sample used to construct the model will influence the result obtained when another population is studied. To correct for this bias, an adjustment factor is included (Skogsvik, 2005, see appendix 2).

2.2 Ratings

Definition	Moodys	S & P	Definition	Moodys	S & P
Investment Grade			**Speculative grade**		
Prime, maximum safety	**Aaa**	**AAA**			
Very high grade/quality	**Aa1**	**AA+**	Highly speculative	**B1**	**B+**
"	**Aa2**	**AA**	"	**B2**	**B**
"	**Aa3**	**AA-**	"	**B3**	**B-**
Upper medium quality	**A1**	**A+**	Substantial risk	**Caa1**	**CCC+**
"	**A2**	**A**	In poor standing	**Caa2**	**CCC**
"	**A3**	**A-**	"	**Caa3**	**CCC-**
Lower medium grade	**Baa1**	**BBB+**	Extremely speculative	**Ca**	**CC**
"	**Baa2**	**BBB**	Maybe in or extremely close to default	**C**	**C+,C,C-**
"	**Baa3**	**BBB-**			
Speculative	**Ba1**	**BB+**			
"	**Ba2**	**BB**	Default		**D**
"	**Ba3**	**BB-**			

Table 3: Credit ratings from Moody's and the corresponding ratings from S&P.

Corporate credit ratings are opinions of an obligors overall financial capacity to pay its financial obligations. Credit ratings focus on the obligor's capacity and willingness to meet its financial commitments as they expire. The long term ratings (for maturities of one year or greater) are divided into *Investment grade* and *Speculative grade* as shown in Table 3. The highest rating, AAA (Standard & Poor) and Aaa (Moody's), is given to companies with extremely high capacity to meet its financial commitments, AA/Aa is given to companies with very high capacity, A/A to companies with strong capacity etc. The lowest rating is given to companies that are highly vulnerable and are very dependent on favorable business, financial and economic conditions in order to meet its financial commitments. In the case of new information or change in the company business environment, the company rating can be reviewed and subsequently be changed (Standard & Poor's 2008), (Moody's Investor Service 2008).

Corporate credit ratings have a broad use. Ratings are used by investors, debt and equity issuers, investment banks, brokers as well as governments for numerous purposes. Debt issuers often need at least one rating from a known rating agency in order to be successful with an issuance. For investors and investment banks, a rating signals the risk premium that should be added on to an investment and for brokers the rating can be used for calculating the risk in their own portfolios. Governments use ratings for regulative purposes, for example according to the new Basel-II agreement (recommendations on banking laws and regulations) banks are only allowed to use ratings from certain rating institutes when calculating their capital requirement. In the US certain bond issuers with a high rating are permitted to use shortened prospectus forms when issuing new debt. Corporate ratings are also used outside the capital markets. A high rating can be used for communicating the entity's creditworthiness to any third party that in some way is exposed to either credit or performance risk when dealing the organization, for example suppliers, customers, joint venture partners and landlords (Gusterman 2008).

The process of assigning credit ratings starts with an inquiry from a company or organization. This is often initiated as a preparation for a debt or equity issue. The rating agency starts with a thorough analysis of the company as well as the industry. In this process, the rating agency uses publicly available information, for example annual and quarterly reports, but it also gains access to non-public information provided by the company. Rating agencies also get access to in-house projections, transaction and legal documents, and have the possibility to interview management. After completing their analysis, a report is presented to a rating committee, consisting of a handful of experienced voting members, along with a suggestion of a certain rating. The report is discussed in the committee, a final decision is reached and the rating is communicated to the company and to the market, conditioned on that the company wishes to make it public. Subsequent years, the rating is reviewed at least once a year (Gusterman 2008).

Average Cumulative Issuer-Weighted Global Default Rates*

	-----Time Horizon (Years)-----				
Rating	**1**	**2**	**3**	**4**	**5**
Aaa	0.000	0.000	0.000	0.035	0.078
Aa1	0.000	0.000	0.000	0.099	0.149
Aa2	0.000	0.010	0.044	0.110	0.211
Aa3	0.018	0.036	0.070	0.123	0.177
A1	0.003	0.082	0.218	0.308	0.377
A2	0.024	0.076	0.206	0.389	0.557
A3	0.034	0.156	0.317	0.429	0.578
Baa1	0.154	0.425	0.749	1.040	1.308
Baa2	0.164	0.450	0.818	1.396	1.882
Baa3	0.329	0.893	1.545	2.280	3.195
Ba1	0.747	1.958	3.460	4.936	6.477
Ba2	0.856	2.403	4.287	6.212	7.977
Ba3	1.929	5.369	9.523	13.671	17.152
B1	3.064	8.135	13.408	18.029	22.986
B2	4.814	10.905	16.308	20.955	24.864
B3	9.525	17.753	25.434	32.257	38.266
Caa1	12.161	23.751	35.108	44.221	51.517
Caa22	20.250	30.286	38.358	45.265	49.376
Caa3	26.482	38.212	45.071	50.421	55.373
Ca-C	33.643	44.631	53.222	58.890	66.743
Investment-Grade	0.073	0.218	0.412	0.635	0.858
Speculative-Grade	4.904	9.793	14.463	18.505	22.080
All	1.681	3.339	4.881	6.179	7.277

* Time period 1993-2006

Table 4: The table shows global default rates between 1993 and 2006. As seen, the default rates are substantially higher for speculative ratings (B1-C) than for Investment grade ratings (Aaa-Ba3). For example a company rated A3 has a 0.034% default probability within one year. The cumulative probability that the company has defaulted in three years time is equal to 0.317%.

The procedure for the different rating agencies is similar, but there are some minor differences. In this thesis, ratings from the two largest ratings agencies, S&P and Moody's, have been used. The most important difference between the rating agencies is that S&P only uses the *probability of default* in their ratings, whilst Moody's uses the product of the *probability of default* and an estimate on the *loss given a default*. However, this technical difference does not impair the transferability of the ratings from the different agencies (Gusterman 2008).

The probability of failure for the different companies is obtained from a historical survey by Moody's covering the years 1993-2006 (Table 4), (Moody's Investor Service 2007). In this thesis the assumption has been made that the ratings from Moody's are equal to the ratings from S&P, subsequently the same probabilities is used for the companies rated by S&P ratings.

Default has a wide definition by the rating agencies, where a default is defined as the failure to pay interest or principal on an obligation on time. This means that an entity might not be in default from a legal perspective, but can still be treated as a default company by the rating agencies.

2.3 CDS

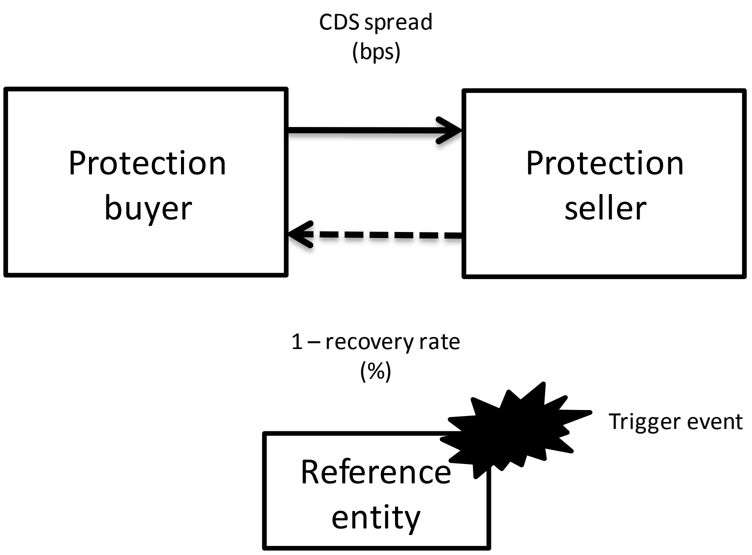


Figure 1: A CDS contract works as an insurance against a default, where the protection buyer pays a premium to the seller and receives a contingent payment if the reference entity defaults. The reference entity is not a part in the contract.

A CDS contract can be compared to an insurance against credit risk. The contract can be used to protect a bondholder against the event of default on the company that has issued the debt (**the reference entity**), see Figure 1. The buyer is the party that receives the protection (**the protection buyer**), and the seller is the party that provides the protection (**protection seller**). The buyer pays a premium (**CDS Spread**) to the seller for the period specified in the contract. When a certain pre-specified credit event (**trigger event**) occurs in the reference entity, for example bankruptcy or restructuring, the protection seller is obliged to settle the obligation with the protection buyer. The compensation is to be paid either by physical settlement or cash settlement, whatever is specified in the CDS contract. In the physical settlement the protection buyer sells the distressed loan to the protection seller at par. In a cash settlement the protection buyer receives cash from the protection seller for the difference between the par value and the value of the distressed bond. The compensation that the protection buyer pays to the protection seller is defined as the CDS spread and is expressed in basis points (bps). A CDS spread of 100 bps means that the premium for protecting a bond will be 100 bps of the face value, equal to 1% per year (Nomura, 2004).

A CDS contract does not have to be used as insurance for a bond that an investor actually own, but it can be used as a way to gain exposure to credit risk without holding any of the reference entity's outstanding debt. A CDS contract can also be entered even though there are no bonds available from the reference entity. In other words, a CDS can be a very effective tool to diversify or hedge a portfolio, or to speculate in future changes in the credit worthiness of an entity.

CDS instruments are today traded over the counter (OTC), which makes it difficult to estimate the size of the market. Every contract is tailor-made to suit the needs of the parties engaged, hence there is no standardized form of the contract and the statistics are not always transparent regarding the conditions in the contract (for example the number of premium payments per year or what is specified as a trigger event). However there is a "Master Agreement" issued by the International Swaps and Derivative Association (ISDA 2008) that is widely used and most CDS contracts are constructed according to this agreement. This agreement specifies and formalizes six trigger events: Bankruptcy, Failure to Pay, Restructuring, Repudiation/Moratorium, Obligation Acceleration and Obligation Default. Market participants usually views Bankruptcy, Failure to pay and Restructuring as the most important events to seek protection from. The most commonly traded CDSs are 5 Year CDS, which offers protection over a five year period (Nomura, 2004). However, in this thesis the 1 Year CDS is used.

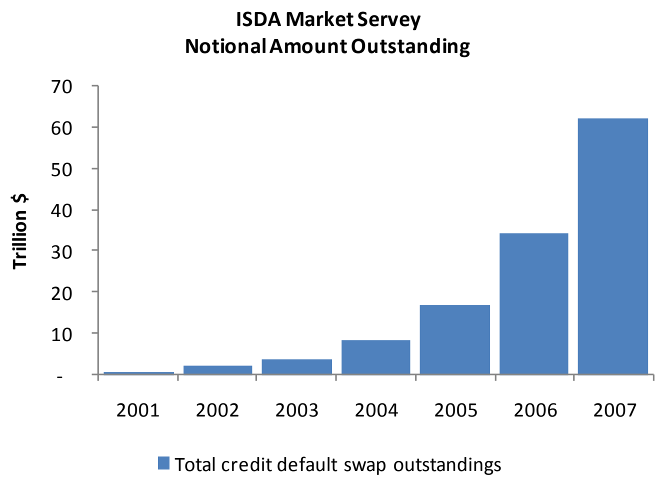


Figure 2: The notional amount of CDS contracts outstanding according to ISDA. The growth has been exponential the last years.

Even though it is hard to find any reliable statistics regarding the CDS market due to the reasons explained above, it is clear that the outstanding market for CDS products has grown substantially during the last years. ISDA's estimation about the size of the market is presented in Figure 2. The largest players on the CDS market are commercial banks, insurance companies, hedge funds and other financial institutions like bond insurers. Figure 3 shows the breakdown of protection sellers by June 2007 (ISDA 2008).

By studying the CDS spread on the market, an implied risk of failure can be calculated. Since the CDS spread changes continuously, the implied risk is continuously updated, which is a strength compared to the other models that are updated with longer intervals.

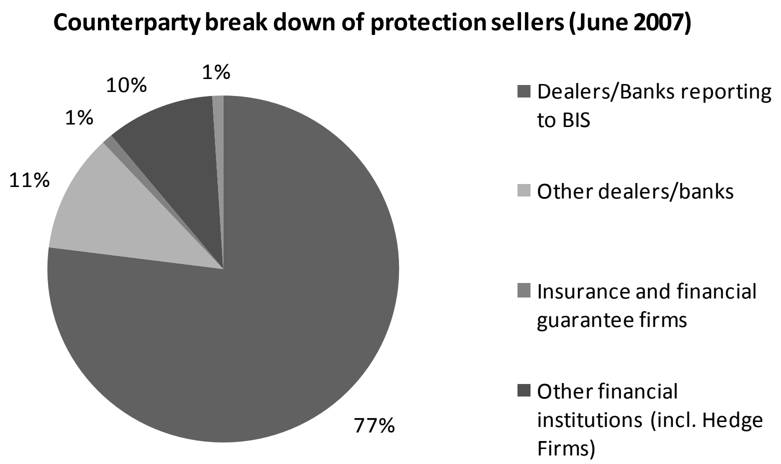


Figure 3: The largest players on the CDS markets are major banks. The banks stand for almost 90% of the protection selling.

Source: BIS, Bank of International Settlements

The model that is used to estimate the implied probability of default from the CDS spread can look fairly complex at the first glance (See Appendix 1).

As a benchmark, one can calculate the default probability (D_{prob}) as:

$$D_{prob}\,(bps) = \frac{CDS\ Spread_{\ bps}}{(1 - Recovery\ rate)}$$

This benchmark model implies that with a 50% recovery rate, the probability of failure is twice the CDS spread. If the CDS spread is 5 bps, and the recovery rate 50%, the probability of default must be 10 bps or 0.1%.

However, the benchmark model is not exact even though it gives a good indication of the implied probability of default. To illustrate the model used in this thesis, a numerical example of a hypothetical CDS trade will be explained.

2.3.1 Numerical CDS Example

Pricing Example

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Month	Discount factor	Survival probability to period (%)	Fixed payment (bps)	Expected value of fixed payments (bps)	PV of fixed payments SEK	Default probability for the period (%)	Expected accrued interest (bps)	PV accrued interest SEK	Expected contingent payment (bps)	PV of contingent payments SEK
				(2) x (3)	(4) x (1)		(3) / 2 x (6)	(7) x (1)	(1-R) x (6)	(9) x (1)
0	1,00000	100,00%	0	0	0,00	0,00%	0,00	0,00	0,00	0,00
3	0,98906	99,50%	25	24,88	2 460,28	0,50%	0,06	6,22	30,00	2 967,17
6	0,97823	99,00%	25	24,75	2 421,12	0,50%	0,06	6,19	30,00	2 934,70
9	0,96753	98,50%	25	24,63	2 382,53	0,50%	0,06	6,16	30,00	2 902,58
12	0,95694	98,00%	25	24,50	2 344,50	0,50%	0,06	6,13	30,00	2 870,81
Pressent Values (PV)				**Sum of PV**	**9 608,43**		**Sum of PV**	**24,69**	**Sum of PV**	**11 675,26**

Value of CDS for protection buyer	
PV of contingent payments	**11 675,26**
PV of expected accrued interest	24,69
PV of expected value of fixed payments	9 608,43
Sum of fixed and accrued interest payments	**9 633,12**
Value of CDS = Contingent - sum of fixed and accrued	**2 042,14**

Input data	
Yearly CDS spread/premium	100
Quarterly payments	25
Discount rate	4,5%
Recovery	40%
Probability of failure	2,0%
Notional amount	1 MSEK
CDS spread implying 0 value of CDS	120
CDS dafault probability implying 0 value	1,65%

Table 5: The assumptions of the hypothetical CDS trade is presented in the box “Input data”. The data is used to calculate the fixed and the contingent leg, and the result is a value of the CDS to the buyer of 2042.14 SEK for protection of a notional amount of 1 MSEK. In an efficient market, this value is driven to 0 by a change in either the assumptions of the probability of failure or the CDS spread.

The example considers a 1-year CDS contract with quarterly payments. The CDS spread is assumed to be 100 bps, the risk-free discount rate is 4.5%, the probability of default is assumed to be 2% and the recovery rate is set to 40 % (Table 5). The recovery rate (R) is the percentage of the face value that a creditor will receive in case of default.

A CDS consists of two parts: a fixed leg of periodic payments, that is the value of the premiums the protection buyer pays, and a contingent leg, the value of the payment that the protection seller has to pay in case of a default in the reference entity.

The first step is to value the fixed leg of periodic payments. These payments are the premiums that are paid quarterly by the protection buyer. To value the fixed periodic payments, start with calculating the expected value of fixed payments (column 4). Then calculate the present value of these payments (column 5). The sum of column 5 gives the present value of all expected periodic payments. In this example the expected fixed periodic payments on a 1 MSEK notional amount summarizes to 9 608.43 SEK. **The second step** is to calculate the present value of the accrued interest that is a part of the fixed leg. If a default occurs, the model expects that such an event happens in the middle of two payment dates, i.e. between two quarters. This means that the accrued payments are calculated as 12.5 bps, half of 25 bps (the quarterly payment). The expected value of the accrued payment for each period is 12.5 bps multiplied by the probability of default for that period (column 7). The present value of the accrued interest is then calculated for each quarter (column 8). In the bottom of column 8 the result of the expected and present value of the accrued interest is summarized resulting in a value of 24.69 SEK. Now, the total present value of the fixed leg, or the present value of the expected payments by the protection buyer over the 1 year term, is 9 608.43 SEK + 24.69 SEK = 9 633.12 SEK. This is the expected present value of what the protection buyer pays to the protection seller for the protection of a notional value of 1 million SEK.

The third step is to calculate the value of the contingent leg. The expected value of the contingent payment, if a default occurs during each period, is (*1-Recovery rate)* multiplied with the probability of default for that period. Assuming a recovery rate of 40%, the expected contingent payments are calculated as 0.6 multiplied by the probability of default of each period (column 9). Then calculate the present value of these values in column 10 and at the bottom of this column a summation of the total present value of the contingent payments is done. This is the present value of the actual contingency that the protection seller guaranties. In this example the present value of the contingent payments are equal to 11 675.26 SEK.

The **forth step** is to calculate the **value of the CDS** for the buyer. This is done by subtracting the value of the fixed leg (fixed payments + accrued interest) from the contingency value.

Value of CDS = PV [expected contingent payment] - PV [fixed leg]=

=11 675.26 - (9 608.43+24.69) = 2 042.14 SEK

This means that the protection buyer is expected to pay 9 633.12 SEK and for that receives protection to a value of 11 675.26 SEK, an estimated positive value of the CDS for the protection buyer of 2 042.14 SEK.

To see this result intuitively, the average default probability over the term of the CDS is 2% per year and with a recovery rate of 40%, the average expected loss per year is: (1-0.40) * 2% = 1.2 %. The CDS spread is 100 bps per year (1%), which means that in this example the protection buyer gets protection against credit risk covering an expected loss of 120 bps. This is a valuable transaction for the CDS protection buyer, as the CDS has a positive value, calculated as 2 042.14 SEK, or 20 bps on a 1 million SEK notional. Using the benchmark model described earlier:

$$D_{prob} = \frac{100}{(1-0.4)} = 1.65\%$$

This is equal to the "*CDS default probability implying 0 value*" in the numerical example (Nomura, 2004).

Since the default probability is an input variable in the model, it is up to both the protection buyer and the protection seller to estimate and assume what rate of probability they believe should be used to determine the CDS spread, the CDS spread at which they are willing to go through with a transaction. In this example the protection seller probably estimates the default probability to be below 1.65%, at which the CDS value will have a positive value for the seller.

The model used to calculate the default probabilities in this thesis calculates the default probability by driving the value of the CDS, in the example 2 042.14 SEK, to zero, while holding all other variables except for the probability of failure fixed which would be the case if the market is efficient. The model uses the following data: a fixed CDS spread, a fixed recovery rate that is dependent upon a given credit rating, a fixed discount rate and a variable default probability that is solved for.

3. Data

3.1 Probit Model

The accounting data used as input in the Probit Model is obtained from income statements, balance sheets and notes from the sample companies' annual reports for the years 2002-2007. All companies in the sample end their fiscal years on 31 of December.

As discussed before the data has to be adjusted for the choice-based sample bias. For this purpose information about the number of limited liability companies (Aktiebolag) with more than 50 employees 2004-2007 was obtained from Statistics Sweden (SCB 2008). From the same source, information about the number of limited liability companies with more than 50 employees that defaulted during the same period was also collected. The a priori probability was calculated as the average of the percentage failure companies for each year between 2004-2007 and was found to be 0.85%.

SCB - Actual Default Rates Companies > 50 employees	2004	2005	2006	2007
Number of companies	2 763	2 810	2 896	3 047
Number of defaults	39	25	17	16
Defaults (in percent)	1,41%	0,89%	0,59%	0,53%
Average defaults 2004-2007	0,85%			

Table 6: Actual default rates according to SCB between 2004 – 2007, for companies with more than 50 employees. Default in this case is defined as bankruptcy reported by the courts.

3.1.1 Probit Model Assumptions

The input data in the Probit Model comes from annual reports, accessed and gathered through company's websites. A second input in the model is the adjustment factor that depends on the a priori probability of default, which is the probability of default in the population. However, when Skogsvik constructed his model, he used a slightly other definition of default, which included voluntary shutdowns and whether government support was provided. The figures from Statistics Sweden only include bankruptcies reported by courts.

3.2 Ratings

The information about the ratings of the different companies is obtained from Moody's web page (www.moodys.com) for Moody's ratings and from S&P's Stockholm office for the ratings of the companies that Moody's do not cover.

3.2.1 Rating Assumptions

For the ratings it is assumed that there is an approximate parity between Moody's and S&P´s ratings, which means that a AA rating by S&P corresponds to a Aa rating by Moody's and vice versa. This is supported by the Basel-II treaty that requires banks to benchmark their internal rating systems to the ratings from the large rating agencies, implying that the rating agencies ratings are comparable. (Gusterman 2008). Furthermore, it is assumed that the historical probabilities about the ratings will be the same in the future and that they are applicable on Swedish companies as well.

Moody's Average Sr. Bond Recovery Rated by Year Prior to Default					
	Year prior to default				
Rating	1	2	3	4	5
Aaa	100,0%	100,0%	100,0%	97,0%	74,1%
Aa	95,4%	62,1%	30,8%	55,3%	41,6%
A	95,4%	54,9%	50,3%	47,7%	48,4%
Baa	48,1%	46,4%	47,3%	43,8%	43,9%
Ba	42,1%	40,8%	40,6%	44,7%	44,2%
B	36,9%	35,9%	37,4%	39,2%	42,3%
Caa-C	31,8%	31,2%	34,9%	39,2%	34,7%
Investment	48,9%	49,8%	47,9%	46,6%	45,5%
Speculative	35,8%	35,6%	37,5%	40,5%	42,3%
All	36,9%	37,5%	39,5%	42,0%	43,2%
* Time period 1982-2006					

Table 7: The average recovery rates from Moody's between 1982 and 2006. A strong rating indicates a high level of recovery once a bond has defaulted and a week rating indicates the opposite.

3.3 CDS

Daily one year CDS spreads (mid, equal to the average of the highest and lowest quote each day) have been downloaded from Datastream for all the companies in the sample between January 1, 2005 and January 1, 2008. This was done in order to measure the probability of default on the same date as the Probit Model data is valid, i.e. the day when the companies close their financial books.

The recovery rate that is used as an input in the CDS Model is depending on the rating assigned by Moody's or S&P to each company. The actual recovery rate is obtained from a study made by Moody's covering average senior bonds between 1982 and 2006 (Table 5). The recovery rates in this study are based on the market prices of a bond in default 30-day post default (Moody's Investor Service 2007). The discount rates used are 3 month STIBOR (Stockholm Interbank Offered Rates) for each period, obtained from Riksbanken (Riksbanken 2008) (see Table 8 for used rates). Risk neutrality is assumed, which means that no risk premium is added and it is assumed that the probability of default is equally distributed throughout the year.

Riksbanken STIBOR Rates	
Date	Discount rate
2008-01-01	4,134%
2007-01-01	3,457%
2006-01-01	2,270%
2005-01-01	2,165%

Table 8: Historical STIBOR rates from Riksbanken.

3.3.1 CDS Assumptions

Concerning the CDS, several assumptions are made. It is assumed that the market is efficient, which means that the CDS spreads represents the market's view on the probability of default. Another assumption is that the investors are risk neutral and therefore no risk premium should be added to the discount rate in the CDS model. It is also assumed that there is no counterparty risk in the CDS contracts. Also no liquidity risk is assumed to be apparent in the CDS market. The Datastream data that has been used in this thesis has not been verified in regard to what credit events are included in the contracts. Therefore it is assumed that all CDS contracts have the same definition of credit events and that the premium payments are made quarterly. Finally, an assumption is made that the CDS spreads obtained from Datastream are correct as well as the historical STIBOR rates from Riksbanken.

4. Results

The results in this section are visualized through several graphs. In order to make the graphs easier to read, some extreme values and outliers have been excluded as they have significantly impacted the comparability of the graphs. In some cases outliers have had a significant impact on the results, therefore both the average and median is presented. The full blue line describes the average while the dashed red line indicates the median. The percentage numbers for the average and median, above or below the lines are the actual observation at the specified date. The individual positions of the companies in the study have been plotted in the graphs to give an indication of the distribution of the sample, and the position of outliers. The actual results of default probabilities for the studied companies in the different periods are attached in Appendix 3.

4.1 Probit Model – Base Case

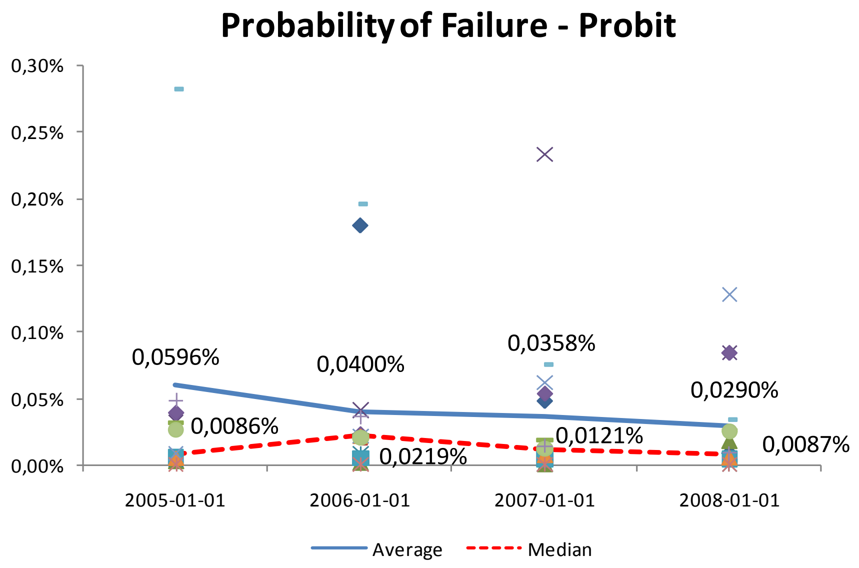


Figure 4: The average probability of default is declining during the observation period. The median shows a slight increase between the first two observations, followed by a decrease. Note that the levels are consistently low during the whole period.

The *average* probability of default in the Probit Model shows a slightly declining trend for all years. The *median* indicates an increase between January 2005 and January 2006, for the other years the results indicates a declining trend. The explanation for the difference between the median and the average between the first two observations is largely due to the outlier ABB, which had a considerably higher default probability of 0.393% in January 200 and much lower for the subsequent years. This has a large impact on the average value. If ABB is excluded from the average, the trend is stable for the entire period. The *average* default probability shifts from a low of 0.029% to a high of 0.060% over the study period and the *median* varies from a low of 0.009% to a high of 0.022%

4.2 Ratings

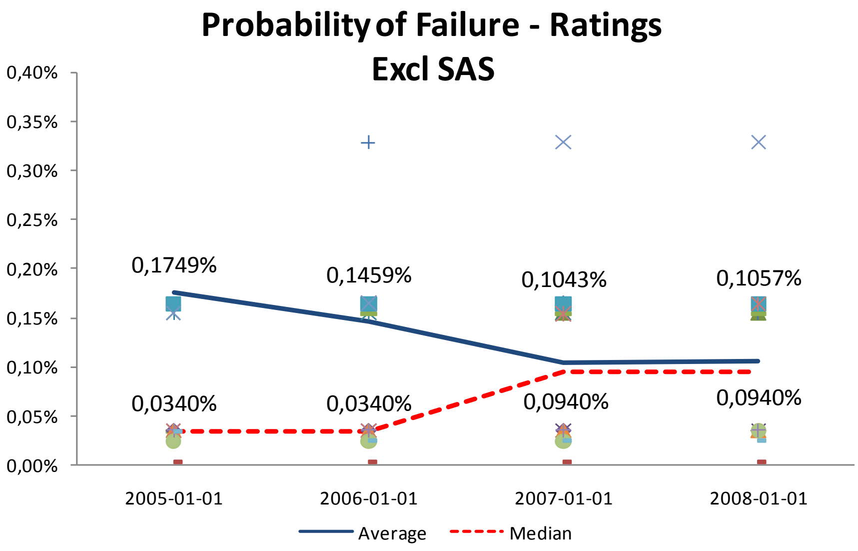


Figure 5: The average probability of default is declining until 2007, when it stabilizes. The median is stable between the two first observations, then increasing and finally stable again. The explanation for this pattern is that the median rating changes one half step from A3 to in between A3 and Baa1, causing the probability to shift accordingly.

The ratings for the sample vary between A1 and B1, which implies a probability of default, based on historical figures, between 0.003% and 3.064%. The company with the lowest rating, and therefore the highest default probability, in all four years was SAS, with an implied default risk of 3.064%. Since SAS therefore has a large impact on the average default probability it has been excluded.The average trend is decreasing for the first two years, and then stabilizing, going from 0.175% in the first period down to 0.106% in the last period. The median results are somewhat different, where the first two periods show the same default probability, 0.034% and the last two periods have the same default probability of 0.094%. The explanation for this abrupt change in the median default probability is that the median rating changes one half step from A3 to in between A3 and Baa1, causing the probability to shift upwards accordingly.

The trend can be described as fairly stable, even though there are a contradiction between the trend of the median and the average trend. However, as explained earlier, the increase in the median is due to the fact that the median rating changes only a half step.

4.3 CDS - Base Case

If the default probabilities given from the Probit Model and the results from the Ratings have been fairly stable, the implied probabilities of default from the CDS model are far more volatile.

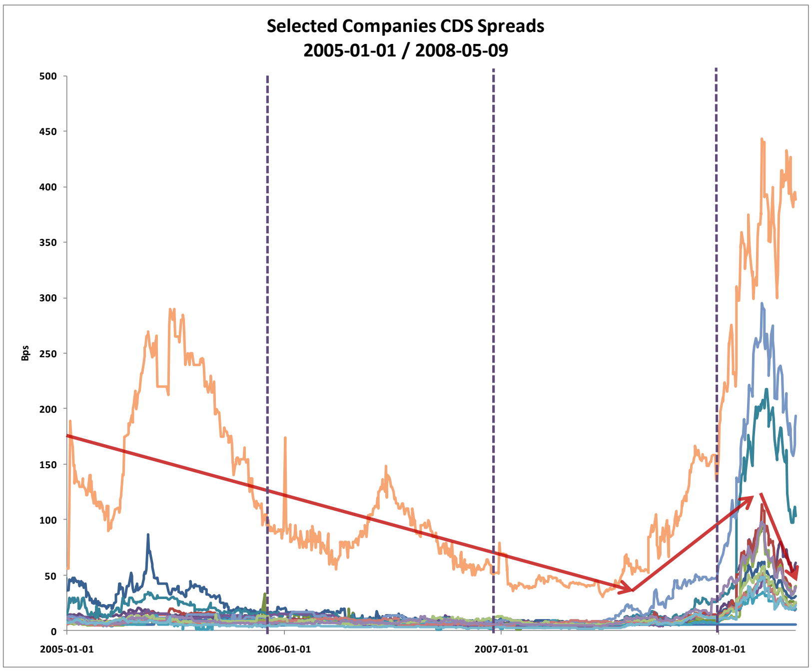


Figure 6: The graph shows the CDS spreads from January 2005 until spring 2008. There is a clear trend of decreasing spreads until the summer of 2007, when the spreads starts to increase significantly. After March 2008, the spreads start to decrease again.

As shown in Figure 6, the CDS spreads for the companies in the sample have fluctuated substantially between 2005 and 2008. It is clear that the trend until the summer of 2007 is sloping downwards, which is evident also if the outlier SAS (yellow line in the graph) is excluded. However, in the summer of 2007 there is a clear break in the trend and the CDS spreads start to rise dramatically. The increasing trend keeps on until mid-March 2008, where the trend yet again is broken and the CDS spreads start to decline.

All observations are made on January 1 each year, and therefore the changes in the CDS spreads after January 2008 are not included. The observations have a clear trend. For the observations made until January 2007, the spreads go down, the first year moderately and the second year almost 30%. Between January 2007 and January 2008 the average spreads go up with more than 150%, from 0.181% to 0.469%.

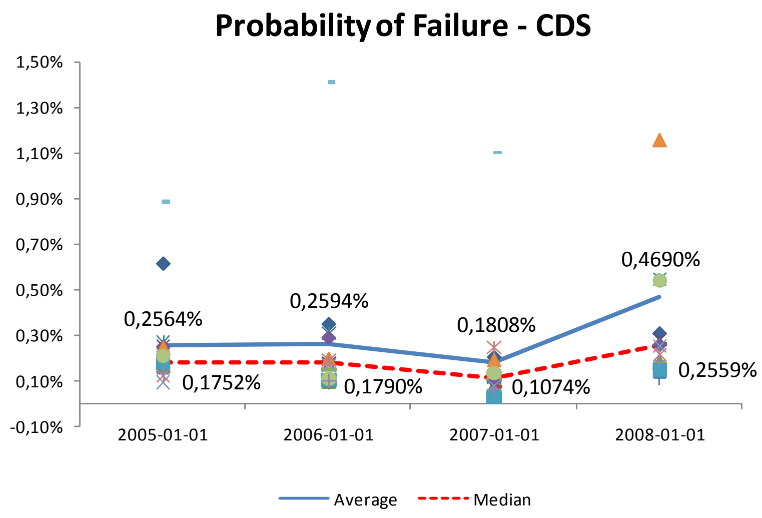


Figure 7: The probability of failure implied by the CDS model shows a stable trend for the first two observations, then a decrease for the third observation, and finally a great increase for 2008.

The average default probability is fairly stable for the first two years, 0.256% and 0.259%. Then a slight decrease can be observed during 2006, to 0.181%. For January 2008 the probability has increased substantially to 0.469%. The median default probability is lower than the average for all years, varying from its lowest point of 0.107% to its highest point of 0.256%, showing a stable trend for the first two years, a decrease the third year and finally an increase the final year.

4.4 Pooling the Observations

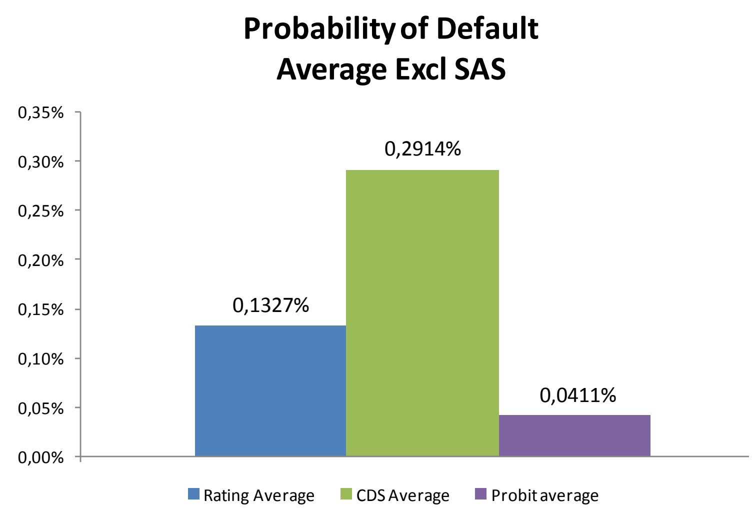


Figure 8: When adding all the observations from each model, it is clear that the CDS Model gives the highest probability of default, and the Probit Model the lowest. The rating model is in between.

Looking at the average of all the observations gathered for each model (60 observations each) there is a clear indication on the difference in the results. The Probit Model gives the lowest levels of probability of default, 0.041%. The Rating Model is roughly three times higher with a default probability level of 0.133% and the highest levels are found by the CDS Model. The CDS Model implies a default probability of the sample companies, when looking at observations over the whole time period, of 0.291%.

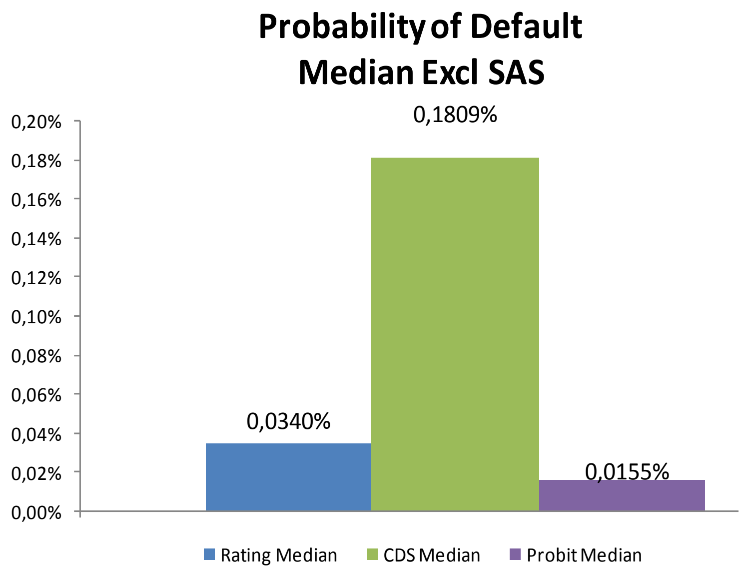


Figure 9: The median shows the same results as the average. The CDS Model is highest while the Probit Model is the lowest

The results are similar when examining the *median* default probabilities for the different models. The Probit Model shows the lowest levels, followed by the rating model and then the CDS Model clearly stands out. The median level is lower for all the models indicating that the average level is clearly affected by outliers and extreme values.

4.5 Summary of Results

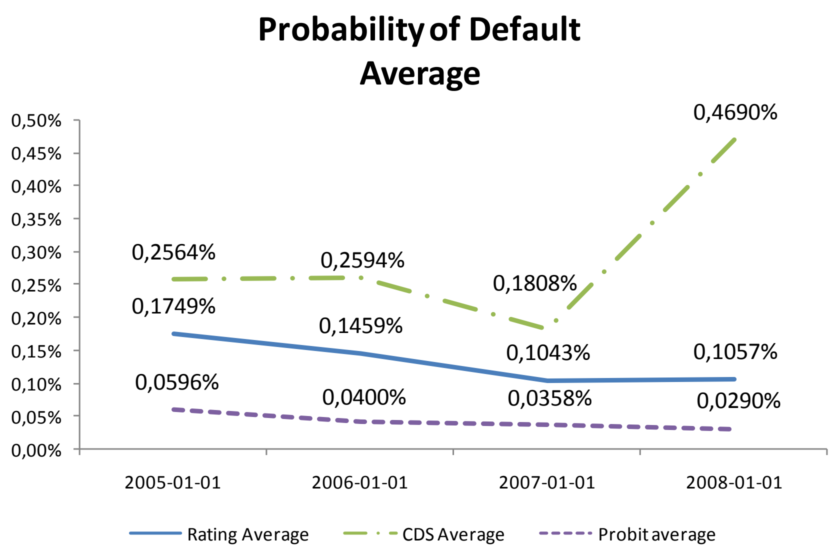


Figure 10: The Probit Model and the ratings shows similar trends. The CDS model is dramatically higher in the last observation period.

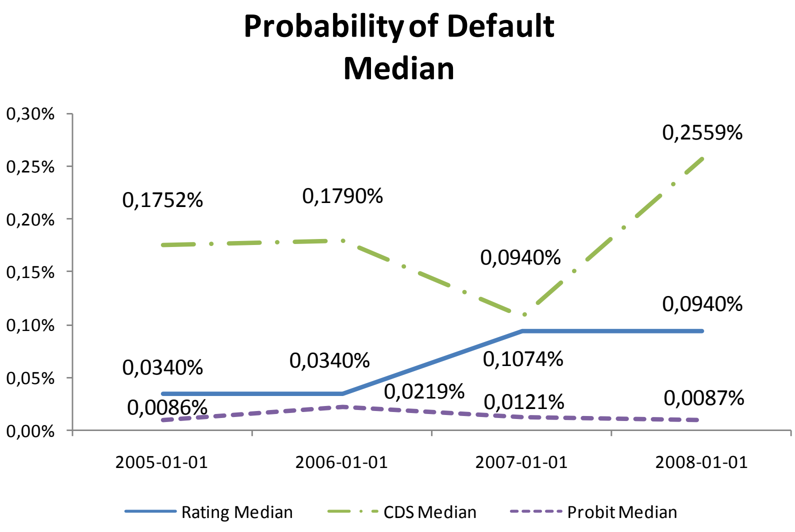


Figure 11: The median CDS probability of default is higher than the Probit Model and rating probabilities.

As Figure 10 and 11 shows, it is possible to identify clear trends of how the default probability has developed over time for the different models. The Ratings and the Probit Model are stable, both when studying the average and median. The CDS Model gives a more volatile result, and shows a substantial increase for the last period.

When the *average* probability of default is compared, it is clear that the lowest levels of probabilities for all periods are obtained from the Probit Model and that the CDS Model gives the highest probability of default.

5. Analysis

5.1 Probit Model – Base Case

The results from the Probit Model implies that the *average* probability of default shows a slight decrease for the whole period, whereas the median implies an increase during 2004 and 2005 followed by decreases during 2006 and 2007. Overall, one has to admit that the *changes* in the default probability in absolute numbers are very small. Even if a downward trend is not clear, the overall trend can be described as stable.

The Probit Model relies only on historical accounting data and the companies in the sample have, due to the last year's strong business cycle, strengthened their balance sheets. Some of the companies, like ABB, experienced some very tough years in the beginning of the new millennium and have since then improved the profitability greatly, which can be seen in the decreasing probabilities given by the Probit Model. The model is also positively related to the average cost of debt, which during the last years has been considerably lower than the historical average (Nyberg Lars 2007). Looking at the context of the results found, the Probit Models shows the lowest levels of default probabilities.

However, the relative level (compared to the other models) of default probabilities is dependent of what a priori probability of default that is used as the adjustment factor. It is possible that the a priori probability that is used in the model is too low, since the time period studied in this thesis is characterized by a strong business cycle, which might have lead to fewer bankruptcies than normal. Another explanation is the fact that the definition of failure used in the Probit Model used in this thesis and the definition used by Skogsvik, are not identical. Skogsvik includes events such as granting government support and voluntary shutdowns, events that are not included in the default definition when adjusting the results with the a priori probability through the adjustment function.

In the Robustness section a further analysis will be done to find what a priori probability is needed in order to get the same probability of default from the Probit Model as the probability implied by the Ratings.

5.2 Ratings

Company Rating Transition

Year	ABB	ATLAS COPCO	ELECTROLUX	ERICSSON	SANDVIK	SCA	SCANIA	SECURITAS
2007/06	→	→	↓	↑	→	→	→	→
2006/05	↑	→	→	↑	→	→	→	→
2005/04	→	→	→	↑	→	↓	→	→

Year	SKF	SWEDISH MATCH	TELIASONERA	STORA ENSO	SAS	VATTENFALL	VOLVO
2007/06	→	↓	↓	→	→	→	→
2006/05	→	↓	→	↓	→	→	→
2005/04	→	→	→	↓	→	↑	→

Table 9: The changes in ratings for the companies in the sample during the years 2005-2007.

The Ratings show a stable trend, which is not very surprising due to the fact that the purpose of the rating systems is to keep them as stable as possible. This is done in order to keep the Ratings predictable for users as well as the company that is rated.

During the four years, only twelve changes in ratings occurred for the whole sample of 60 observations. Among the re-rated companies some started the period with low ratings due to financial problems in the past (for example ABB and Ericsson). Five of the twelve changes were upgrades (three for Ericsson and one each for Vattenfall and ABB), and seven out of twelve were downgrades (two each for Stora Enso and Swedish Match and one each for TeliaSonera, SCA and Electrolux), see Table 9.

There are two different trends in the study, the average default probability is declining, and the median is rising, which seems like a contradiction. The explanation is that there are differences between how many percent the probability of default changes between ratings, companies that were upgraded decreased their probability of default more than the companies that were downgraded.

The conclusion is that the probability of default implied by the Ratings has been stable during the study period, showing a slightly increasing trend with more ratings being downgraded than upgraded.

5.3 CDS – Base Case

The CDS spreads have been volatile during the study period, as shown in Figure 12. In the CDS Model, a spread change will have a large impact on the implied probability of default. Given that all input variables are fixed, a change in the CDS spread will change the default probability. As a result, volatile prices will give rise to large changes in the probability of default. The underlying declining trend indicated in the first three periods, from January 2005 to January 2007, has probably the same explanation as in the Probit and the Rating Models, where a favorable business cycle translates into lower probability of default and consequently the price for insurance against default, the CDS spread should be low. When comparing the results from the CDS Model to the results from the Probit Model and the Ratings, the trends are similar between January 2005 and January 2007 with stable or slightly declining probabilities. However, in 2007 the trend is increasing for the CDSs, and the probability of default is significantly higher in the CDS Model than in the other two models.

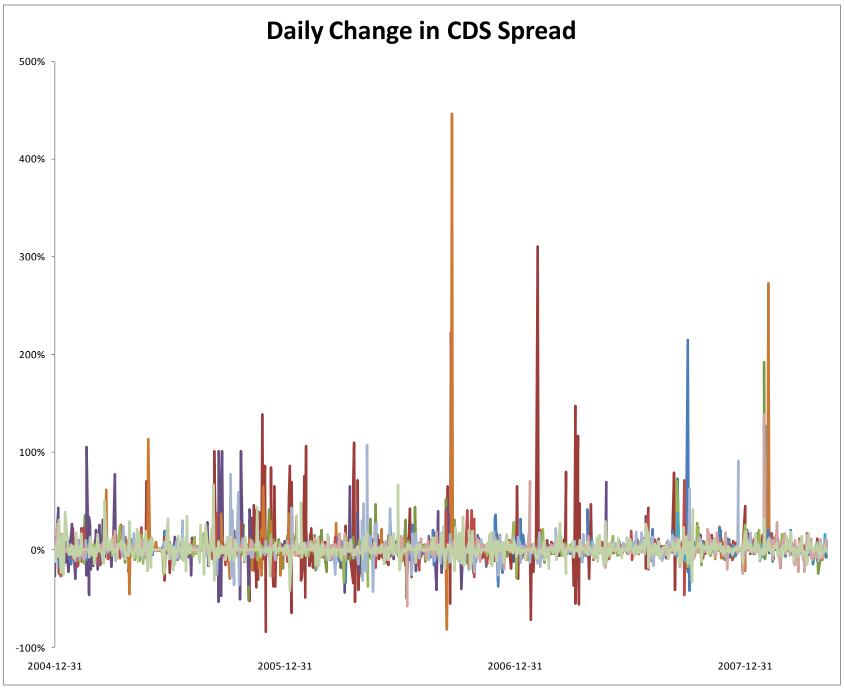


Figure 12: The data shows that there are very large swings in the daily changes for the CDS spreads. Where the average change for the 15 companies in the sample on some days can reach up to 450% and often lies on more than 60%.

Since the model uses CDS spreads from the beginning of each year/beginning, the extreme increase and the following decrease in the CDS spread that has taken place in the spring of 2008 is not included in the regular study period. However, as a part of the Robustness test of the model, this will be tested and CDS spreads as of March 31 will be analyzed (See section 6.5).

5.4 Explanations to the CDS Increase

A number of possible explanations to the sharp increase in the probability of default between January 2007 and January 2008 have been identified.

5.4.1 Re-pricing of Risk

In the last couple of years the interest rates have been historically low and there has been an oversupply of credit in the economy (Wachovia Economics Group 2007). In line with this investors demanded, until June 2007, very low premiums for risk (here defined as the premium demanded for taking on the credit risk from someone else), as seen in the sample data (see Appendix 4). As an example, for a bond issued by SKF with an A3 credit rating, the credit risk could be transferred from the bondholder to a protection seller for a premium as low as 1.32 bps on December 11, 2006, equal to 0.013% on the outstanding notional amount of debt per year (Appendix 4). This is a noticeable low level and implies that the protection on a one year bond issued by SKF should trade only a couple of basis points above a corresponding government bond, meaning that the probability of default for SKF is only slightly higher than the probability of default for a Swedish government bond.

In the second half of 2007 the environment changed, mainly due to the sub-prime crisis which resulted in a major decrease in the appetite for risk and a subsequent increase in the cost of risk. Since the start of the credit crisis the cost of risk has been aggressively reprised, which is clear in the graph over the CDS spreads (Figure 6). The effect of this has been observed in a number of areas: increasing interbank rates due to the unwillingness to lend money between banks, tougher terms for corporate financing and a reduced risk in banks credit portfolios. (Nyberg Lars 2007)

Swedish banks, which have been excluded from the sample of companies studied in this thesis, have been affected by the increase in the cost of risk and speculations of suffering from large write downs connected to the credit crisis. In an environment characterized by a high degree of uncertainty, investors demand higher premiums to take on new risk. This means that banks, which are involved as counterparties in most CDS trades, demand higher returns in order to sell protection, leading to larger CDS spreads. This leads to higher CDS spreads because no one is willing to sell protection, unless the premiums are high. (World Economic Forum 2008)

Most participants would argue that Swedish companies are not directly influenced by this crisis. However, since the market is increasing its overall risk awareness, and CDS instruments are products that transfer risk from one party to the other, CDS prices have been influenced. This reasoning explains why the CDS spreads has increased so much and it also indicates that the actual or underlying default probability, as measured by the Probit Model or Rating agencies has not changed as substantially as the CDS Model claims. Instead it is the re-pricing of risk and risk aversion that has driven up the CDS spreads, and since the CDS Model uses the spreads to calculate the probability of default, the result is an indication of higher risk in the companies. However, that might not be the case: what look like higher default probabilities for individual companies, is only an effect of investors' unwillingness to take on risks.

5.4.2 Real Increase in Default Probability

Since 2003 Sweden has been in an economic upturn where Swedish companies have delivered strong earnings and strengthened their balance sheets and cash reserves. This has reduced the risk for companies going into default. However, the economic outlook is not as bright as it has been the last years. This means that with an increased fear for a recession or a downturn the underlying risk of default has increased. As CDS instruments are traded on the market and are priced on future expectations a change in the economic environment will have impact on the cost of buying protection. It seems then like the market expects a worse scenario than the rating institutes do, hence the implied probability of default has become higher.

5.4.3 Counterparty Risk

The CDS model assumes that there is no counterparty risk. However, in all derivative contracts, there is a risk that the counterparty will not be able to fulfill its obligations, and in the case with CDS products it is the protection buyer that stands the risk that the protection seller of a CDS contract cannot pay the face value of the bond, if the reference entity defaults. On the CDS market, as in most other derivative markets, the counterparty is often large commercial banks and insurance companies, as well as other financial institutions and hedge funds. The problem today is that none of these institutions can be treated as a risk-free counterpart, even when dealing with well-known international banks the counterparty risk is far from zero. One implication of this could be that investors are not sure if they actually will get the protection that they seek and pay for and, as a consequence, they step out of the market. This creates illiquidity on the CDS market, which causes the observed prices on the market to be unrepresentative for the perceived risk. (Barclays Capital 2008)

5.4.4 Speculation

A large portion of the trades in credit derivatives, including CDS, is driven by speculation rather then the need for actual default protection. In this case it is not investors, banks or insurance companies that hedge their portfolios but rather hedge funds and other risk taking investors that speculate in the rise or decrease of CDS spreads, possibly in relation to changes in credit ratings which changes the implied probabilities. Since CDS products are estimations of debt default, traders have increasingly started to speculate in shifts in credit quality. As investors do not have to own the underlying asset and only pay the CDS spread quarterly it is possible to build up highly leveraged position for a reasonable low capital binding.

5.4.5 Liquidity

Since the CDS market is made over the counter, the liquidity risk is higher for a CDS than for many other instruments. One explanation for the price changes could be the lack of liquidity in the market, since low liquidity means that there is no fair market price. Hence the implied probability of default which is calculated from the CDS spread will not reflect the market's view of default probability. The liquidity risk has also risen dramatically after the subprime crisis, since many banks have become increasingly risk averse which fuels the illiquidity in the market (Simon Johnson, IMF 2008).

5.4.6 Market Inefficiency

One explanation to the increase in CDS spreads could be that the CDS market is inefficient. This means that the CDS spreads observed are not concurrent with the underlying default rate but rather is a function of illiquidity and speculation or some other factor. In this case the results obtained when using the CDS Model are not correct and one has to rely on default probabilities estimated in other ways.

6. Robustness Checks

Since the models used are very depending on the assumptions that are made, this section will test the robustness of the models by changing the assumptions and compare the results to the "base cases", the cases before the changes.

Some tests will also be made in order to see what assumptions has to be made in order to get the results from the Probit Model and the CDS model consistent with the results from the Rating Model. The rationale behind this is that the assumptions made in the Rating model is fewer, hence this model is suitable for a benchmark model.

6.1 Robustness Check 1- Change in Probit Model a priori Probability of Default to 1%

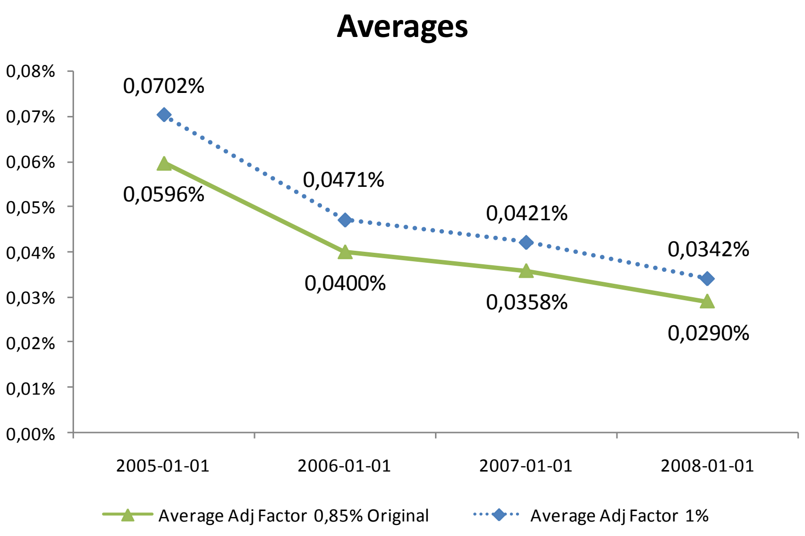


Figure 13: When the a priori probability of failure is changed from 0.85% to 1%, the probability of failure increases.

In this test, the a priori default probability for the population used in the adjustment formula for the Probit Model is changed from 0.85% to 1%. The reason for this test is, as earlier explained, the definition of default in the Probit Model differs from the definition used in Skogsvik's model, and in order for the Probit Model to be consistent with Skogsvik's model the adjustment factor should be higher than the 0.85% used in the base case.

As Figure 13 shows, the average default probability increases for all years when the adjustment factor is changed. The change for each year is equal to 18%, the same change as in the a priori default probability (from 0.85% to 1.00%). The probability of default has a 1:1 relationship with the a priori probability used in the adjustment factor. As a consequence, the change in default probability is not affected by the change in adjustment factor, because of the 1:1 relationship described above. Therefore, the changes between the different observations will, in terms of percent, remains constant.

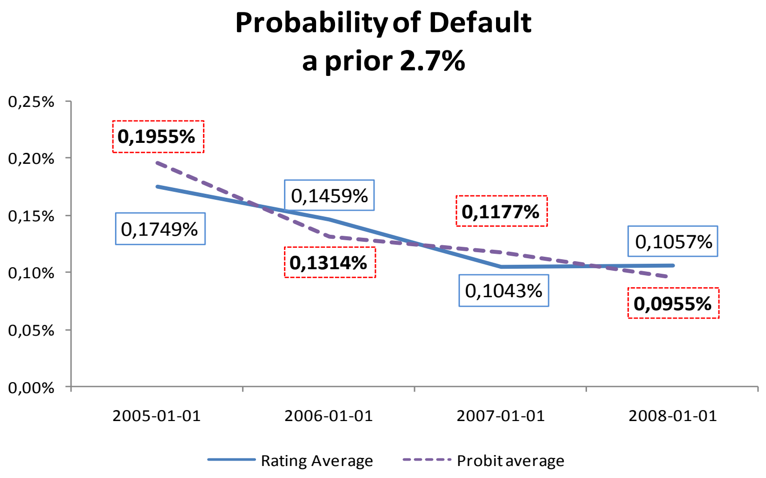


Figure 14: In order to get the Probit Model and the ratings equal, the a priori probability has to be in the area of 2.7%

In order to make the results from the Probit Model in line with the implied default probability from the Ratings, the a priori probability is calculated to be in the area of 2.7%. This is much higher than the actual figures collected from SCB. However, to estimate the number that the Probit Model and the Ratings has to be adjusted with is outside the scope of this thesis.

6.2 Robustness Check 2- Change in Recovery Rate in the CDS Model

This is a check of how the CDS model and the implied probability of failure are affected by a change in the assumed recovery rate.

In the Base Case, the recovery rate is dependent on each company's credit rating. A company with an Aa rating is assumed to have a 95.4% recovery, a company with an A rating is assumed to have a 46.4% recovery rate etc, see Table 4. This assumption might have a substantial impact on the results of the model, and in order to test this all companies are given the same recovery rate for all periods. The recovery rate used is a standard 40% recovery rate, which is a rate that is used in many models (Gusterman 2008). The result from the test is a higher probability of default when using the fixed 40% recovery rate, although the change is not very large (see Figure 15). The reason for the increase in default probability is that the average recovery rate in the base case is higher than 40% (in the base case the average recovery rate is 45.93%). When the recovery rate is lower and the CDS spread is unchanged, the protection buyer will pay the same price on the notional amount of debt. Because of a lower expected recovery rate, the protection seller will risk more at a default, in the base case 54.04% (1-45.96%) of the face value, compared to 60% (1-40.0%) with the lower recovery rate. Hence, the protection seller will only participate in the transaction, given the CDS spread, if the default probability has decreased to counterweigh the decreased recovery rate.

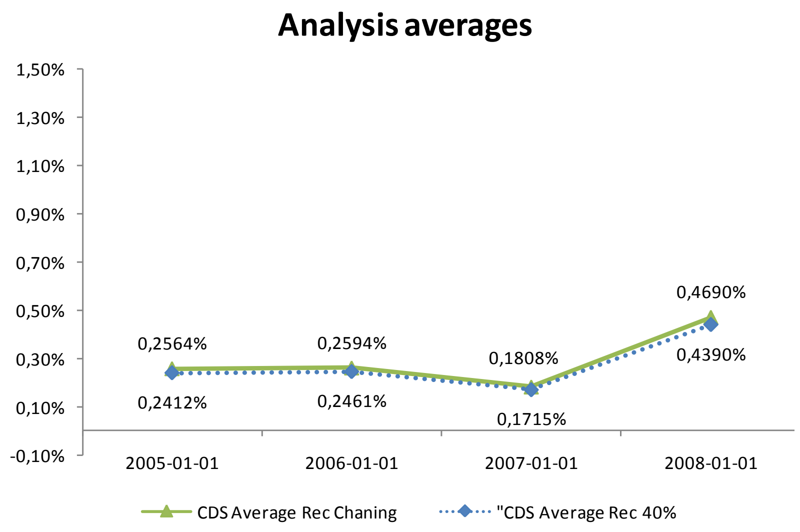


Figure 15: There is only a slight difference when using a fixed recovery rate of 40%. The largest difference is for the last observation.

As the graph shows the average probability of failure for the last period (Figure 15) changes, from 0.469% to 0.439%.The trend of lower probabilities is also evident for the other observations, but the change is largest in the last period. The same trend is evident when looking at the median.

Finally, a test is made to find what recovery rate is needed in order to get the same level of default probability in the CDS Model as in the Ratings. This is found to be somewhere between 10% and 20%, however, the trend with the sharp increase the last year is constant. Since a recovery rate of 20% is much lower than what could be expected to be an average for our sample, this indicates that there must be other explanations for the difference between the default probability given by the Ratings and the CDS model.

The conclusions that we draw from this test is that the change in recovery will affect the model and the levels of probability of default, but the underlying trends will stay the same.

6.3 Robustness Test 3 - Change in Risk Premium, Risk Free Rate +5%

This robustness test examines how an increase in the discount rate affects the default probability in the CDS model.

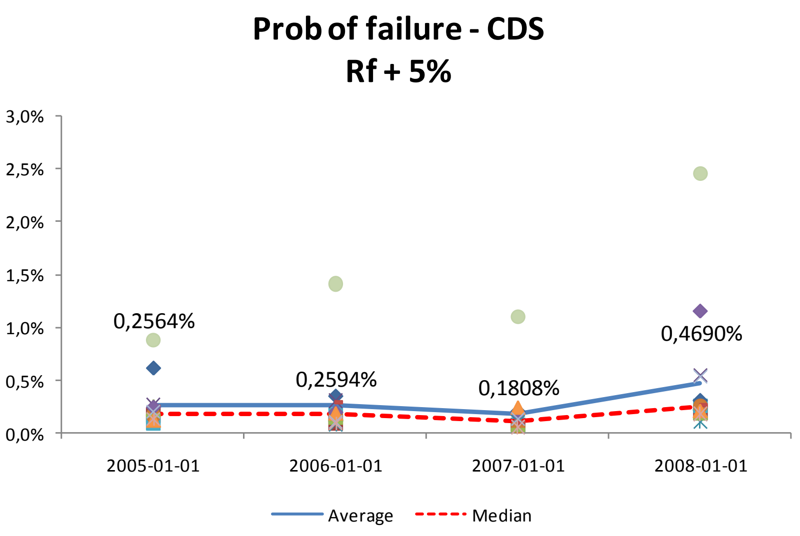


Figure 16: There is no visible difference when adding 5% to the risk free interest rate in the CDS Model in comparison with the Base Case, see Figure 7. The explanation is that the model assumes a zero counterparty risk, and therefore it is not possible to add a risk premium to the interest rate without rebuilding the model.

An additional 5% is added to the risk free rate. The result is that the average CDS default probability remains stable, see Figure 16.

Finally looking at the change in default probability the additional 5% on the risk free discount rate does not have any impact on the change in probability of failure.

The conclusion from this test is that there is a negligible change in the default probabilities due to an increase in the discount rate with 5%. From the test it is evident that the increase in CDS spreads cannot be explained by any change in the discount rate. This is also evident when looking at the benchmark model, where the risk free rate is not included.

$$D_{prob}\,(bps) = \frac{CDS\ Spread\ _{bps}}{(1 - Recovery\ rate)}$$

The model assumes that there is no counterparty risk; hence it is not possible to adjust for such a risk by increasing the discount rate. If one wishes to adjust for counterparty risk, the model has to be reconstructed and different discount rates must be used for the two legs in the CDS contract. In this model, both legs are discounted with the same interest rate, and a rise in the interest which reduces the present value of one leg, is offset by a reduced present value in the other leg. However, there is a small effect on the present value of the accrued interest, but this is such a small change that it will not affect the implied probability.

6.4 Robustness Test 4 - Change in CDS Spread with +10%

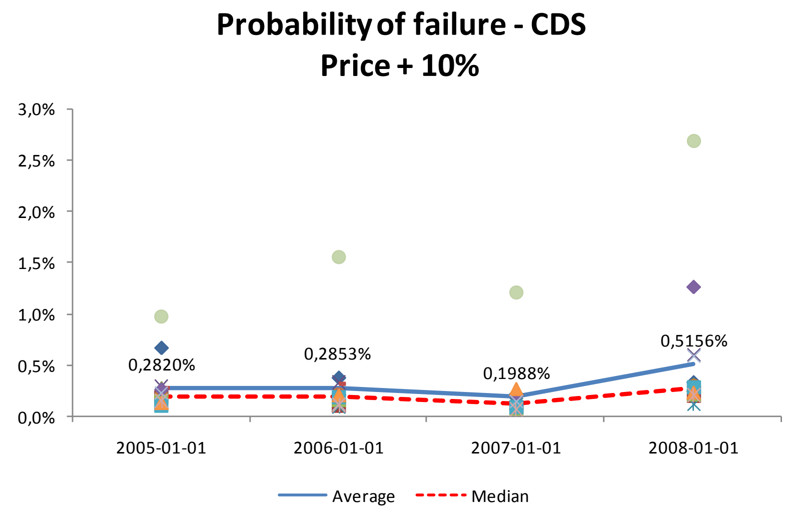
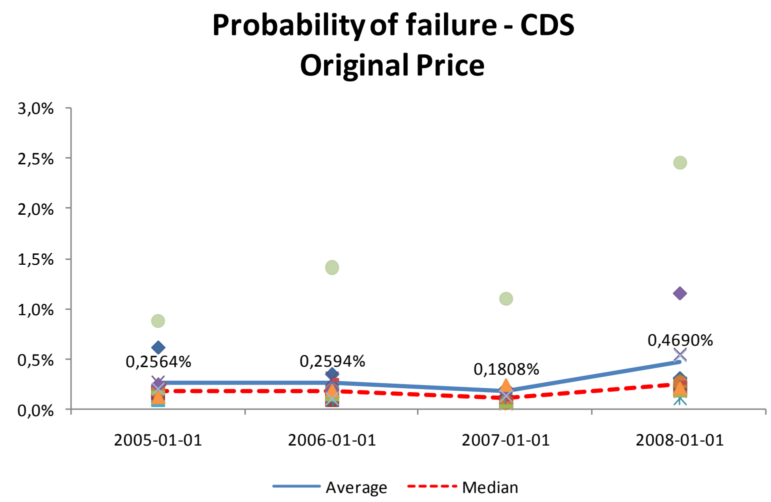


Figure 17 and 18: An increase with 10% on the CDS spread causes the implied probability of failure to increase 10% as well.



This robustness test examines how the CDS probability of failure changes if the CDS spreads increase with +10% compared to the Base case. Not surprising, the probability of failure increases as the CDS price goes up (see Figure 17 and 18), with exactly the same percentage as the increase in the price. Hence, the 10% increase in the test, causes the probabilities to go up with 10% as well.

As a conclusion, there is a 1:1 relationship between the change in CDS spread and the change in the implied probability of default, causing the trend to be stable.

6.5 Robustness Test 5 - CDS Spread from March 31 instead of January 1

This test aims to examine the implication of what date the observations are made. The Probit Model uses the numbers from annual reports dated December 31. However, the annual reports are not available to investors immediately, meaning that if a comparison is made between the Probit, the CDS and Rating models, it should be done when all models has access to the same information. The result can otherwise be that important information in the annual report are taken into account in the Probit Model, but not when the CDS spreads are set or the ratings assigned. To test if this will have an impact on our conclusion, a test is made where the CDS data and the ratings are observed on March 31, a date when most of the annual reports are available.

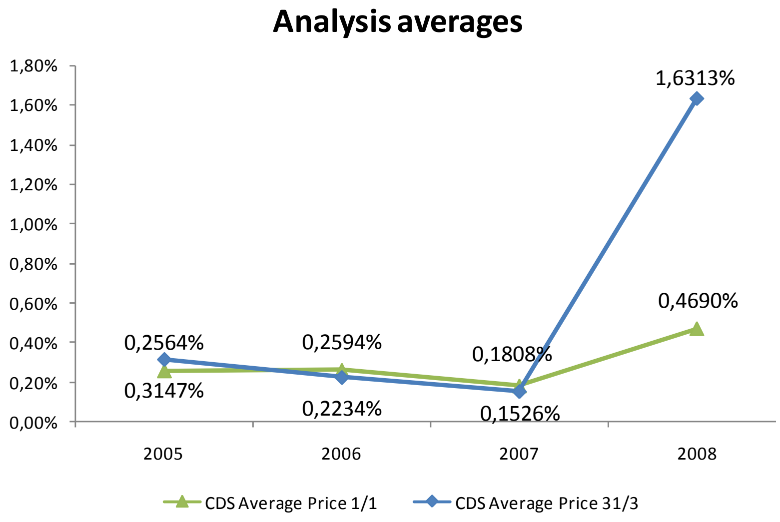
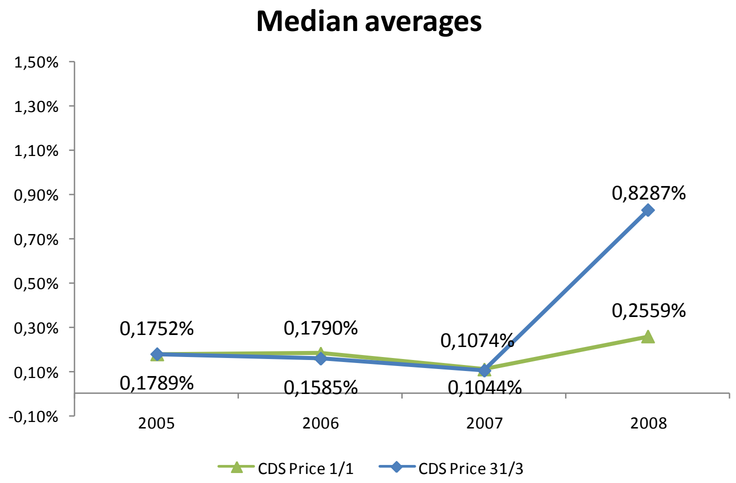


Figure 19 and 20: There is no systematic change in the probability of default when the observations are made on March 31 instead of January 1.



There is only one rating transition during the first quarter of all years, ABB was upgraded on January 21, 2008. This affects the median and average probability failure moderately. On the CDS implied probability the effects are larger. When the prices increase and all other variables are held constant, the implied probability will be higher as well. For both the median and the average, the differences for the first three observations are very small. In 2008, the difference is substantial, 0.4690% in January compared to 1.6313% for March when looking at the averages and 0.2559% to 0.8287% for the median (see Figure 19 and 20).

The conclusion from this test is that there is no systematic difference when measuring the probability of default in January or March and the large difference for 2007 must have another explanation.

7. Discussion

For each of the sample companies four observations, from January 2005 to January 2008, have been collected, a total number of 60 observations for each model. Therefore it is reasonable to be able to draw some conclusions from the study. If this study is made in a few years, when more CDS data is available and more observations can be collected, it would be desirable to extend the analysis using more extensive statistical models.

One possible explanation for the difference in the levels of default probabilities between the models could be that the models have different definitions of default. The rating agencies use a definition where a company is in default if it is late on one single payment. The CDS contract can cover various events which include more events then the Rating agencies. In the Probit Model, Skogsvik's definition of default is different from the one used in this thesis, due to the lack of available data. The Robustness test indicated that in order to reach the same default probability for the sample companies as the one given by the Raging agencies the a priori adjustment factor had to be in the level of 2.7% which is considerably higher than the level indicated by SCB.

8. Conclusion

The purpose of this thesis was to examine three different methods for estimating default probabilities for large Swedish companies. This has been done by calculating and analyzing default probabilities for the Probit Model, Credit Ratings and the CDS Model. The results found have been generalized and we have examined the average and median levels for the different models. The aim was not to give answers to the exact default probability of each company, but to see what levels of default probability the models estimate on average and what trends, if any, could be identified.

In light of the dramatic increase in CDS spread over the later part of the study period (2007-2008) it is obviously interesting to examine if the underlying default probability for large Swedish companies have actually increased to the same extent. This study shows that when holding all other assumptions in the CDS Model fixed the default probability increases substantially in the last period, after having been on a reasonably low level in the past. However when comparing the results from the CDS Model to those of the Probit Model and Ratings it is obvious that the increase is due to more factors than a sheer increase in the underlying default probability. A number of possible and reasonable explanations to this phenomenon have been discussed and it is very likely that a mixture of de-risking, ill-liquidity in the market, speculation and market failure, due to the credit crisis, is behind the exceptional increase in CDS spreads.

Both the Probit Model and the Ratings shows a stable trend over the study period, and overall estimate much lower levels of default probability for the sample. As seen in the test where all the 180 observations are pooled the Probit Model shows the lowest levels of default probability. The Rating agency is about three times higher than the Probit Model and the CDS Model indicates an even higher level of default probability in the sample. Also when looking at the other tests the Probit Model gives the lowest probability of default levels for all years.

Since none of the companies in the sample has defaulted during the study period, one could claim that the Probit Model, which estimated the lowest levels of default probability, has given the most accurate levels when it comes to describing the risk of default of the sample.

9. Bibliography

Altman, E. I., 1968, “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy”, The Journal of Finance, No. 4, pp. 589−609.

Barclays Capital. "Counterparty risk in credit markets." 2008.

Gusterman, Alexander, interview by Anders Skarle. *Standard & Poors's* (04 17, 2008).

Hull, J. C. and A. White,. "Valuing credit default swaps I: No counterparty default risk." *Journal of Derivatives, vol. 8, no. 1*, 2000: 29-40.

ISDA. 05 14, 2008. www.isda.org (accessed 05 14, 2008).

Lundén, Erik, and Peter Rimbäck. "Identifying bankruptcies: an empirical study of Swedish labour intensive IT companies." *Master Thesis in Accounting and Financial Management*, 2003: 0-60.

Moody’s Investor Service. *Moody’s.* 05 14, 2008. www.moodys.com (accessed 05 14, 2008).

Moody’s Investor Service. "Special Comment: Corporate Default and Recovery Rates, 1920-2006." 2007.

Nomura Fixed Income Research. "Credit Default Swap (CDS) Primer." 2004.

Nyberg Lars. "Risksbanken."03 13, 2007. www.riksbanken.se (accessed 05 14, 2008).

Riksbanken. 05 14, 2008. www.riksbanken.se (accessed 05 14, 2008).

SCB. *Statistic Sweden.* May 10, 2008. www.scb.se (accessed May 10, 2008).

Simon Johnson , IMF. "Straight Talk: Inside Risks." *Finance and Development*, 2008.

Skogsvik, Kenth. *Prognos av finansiell kris med redovisningsmått: en jämförelse mellan traditionell och inflationsjusterad redovisning.* Stockholm: Ekonomiska forskningsinstitutet vid Handelshögsskolan i Stockholm, 1987.

Standard & Poor’s. *Default, Transition, and Recovery: 2007 Annual Global Corporate Default Study And RatingTransitions.* McGraw-Hill, 2008.

Wachovia Economics Group. "SPECIAL COMMENTARY Subprime Lending as Classic Credit Cycle." 2007.

World Economic Forum. *Global Risks 2008: A Global Risk Network Report: World Economic Forum.* World Economic Forum, 2008.

Annual reports have been gathered for the following years: 2002, 2003, 2004, 2005, 2006 and 2007:

ABB – www.abb.se

Atlas Copco – www.atlascopco.se

Electrolux – www.electrolux.se

Ericsson – www.ericsson.se

Sandvik - www.sandvik.se

SAS – www.sas.se

SCA – www.sca.se

Scania – www.scania.se

Securitas – www.securitas.se

SKF – www.skf.se

Stora Enso – www.storaenso.se

Swedish Match – www.swedishmatch.se

TeliaSonera – www.teliasonera.se

Volvo – www.volvo.se

Vattenfall – www.vattenfall.se

10. Appendix

10.1 Appendix 1: CDS Pricing according to Nomura

This appendix is taken directly from an article by Nomura Fixed Income Research, available through:

www.securitization.net/pdf/content/Nomura_CDS_Primer_12May04.pdf

A typical CDS contract usually specifies two potential cash flow streams – a fixed leg and a contingent leg. On the fixed leg side, the buyer of protection makes a series of fixed, periodic payments of CDS premium until the maturity, or until the reference credit defaults. On the contingent leg side, the protection seller makes one payment only if the reference credit defaults. The amount of a contingent payment is usually the notional amount multiplied by (1 – R), where R is the recovery rate, as a percentage of the notional. Hence, the value of the CDS contract to the protection buyer at any given point of time is the difference between the present value of the contingent leg, which the protection buyer expects to receive, and that of the fixed leg, which he expects to pay, or,

Value of CDS (to the protection buyer) = PV [contingent leg] – PV [fixed (premium) leg]

In order to calculate these values, one needs information about the default probability (i.e. credit

curve) of the reference credit, the recovery rate in a case of default, and risk-free discount factors (i.e. yield curve). A less obvious contributing factor is the counterparty risk. For simplicity, we assume that there is no counterparty risk and the notional value of the swap is $1 million.

First, let's look at the fixed leg. On each payment date, the periodic payment is calculated as the annual CDS premium, S, multiplied by di, the accrual days (expressed in a fraction of one year) between payment dates. For example, if the CDS premium is 160 bps per annum and payments are made quarterly, the periodic payment will be:

$$d_i S = 0.25(160) = 40 \text{ bps}$$

However, this payment is only going to be made when the reference credit has NOT defaulted by the payment date. So, we have to take into account the survival probability, or the probability that the reference credit has not defaulted on the payment date. For instance, if the survival probability of the reference credit in the first three months is 90%, the expected payment at t1, or 3 months later, is:

$$q(t_i)d_iS= 0.9(.25)(160) = 36 \text{ bps}$$

whereq(t) is the survival probability at time t. Then, using the discount factor for the particular payment date, D(ti), the present value for this payment is D(ti)q(ti)Sdi. Summing up PVs for all these payments, we get

$$\sum_{i=1}^{N} D(t_i)q(t_i)Sd_i \qquad \text{-- (1)}$$

However, there is another piece in the fixed leg - the accrued premium paid up to the date of default when default happens between the periodic payment dates. The accrued payment can be approximated by assuming that default, if it occurs, occurs at the middle of the interval between consecutive payment dates. Then, when the reference entity defaults between payment date ti-1 and payment date ti, the accrued payment amount is Sdi/2. This accrued payment has to be adjusted by the probability that the default actually occurs in this time interval. In other words, the reference credit survived through payment date ti-1, but NOT to next payment date, ti. This probability is given by

{q(ti-1)- q(ti)}.

Accordingly, for a particular interval, the expected accrued premium payment is

{q(ti-1)- q(ti)}S di/2.

Therefore, present value of all expected accrued payments is given by

$$\sum_{i=1}^{N} D(t_i)\{q(t_{i-1}) - q(t_i)\}S\frac{d_i}{2} \qquad \text{--(2)}$$

Now we have both components of the fixed leg. Adding (1) and (2), we get the present value of the fixed leg:

$$PV\ [fixed\ leg] = \sum_{i=1}^{N} D(t_i)q(t_i)Sd_i + \sum_{i=1}^{N} D(t_i)\{q(t_{i-1}) - q(t_i)\}S\frac{d_i}{2}. \qquad \text{--(3)}$$

Next, we compute the present value of the contingent leg. Assume the reference entity defaults between payment date ti-1 and payment date ti. The protection buyer will receive the contingent payment of (1-R), where R is the recovery rate. This payment is made only if the reference credit defaults, and, therefore, it has to be adjusted by {q(ti-1)- q(ti)}, the probability that the default actually occurs in this time period. Discounting each expected payment and summing up over the term of a contract, we get

$$PV\ [contingent\ leg] = (1 - R)\sum_{i=1}^{N} D(t_i)\{q(t_{i-1}) - q(t_i)\} \qquad \text{--(4)}$$

Plugging equation (3) and (4) into the equation in the beginning, we arrive at a formula for calculating value of a CDS transaction. When two parties enter a CDS trade, the CDS spread is set so that the value of the swap transaction is zero (i.e. the value of the fixed leg equals that of the contingent leg). Hence, the following equality holds:

$$\sum_{i=1}^{N} D(t_i)q(t_i)Sd_i + \sum_{i=1}^{N} D(t_i)\{q(t_{i-1}) - q(t_i)\}S\frac{d_i}{2} = (1-R)\sum_{i=1}^{N} D(t_i)\{q(t_{i-1}) - q(t_i)\}$$

Given all the parameters, S, the annual premium payment is set as:

$$S = \frac{(1-R)\sum_{i=1}^{N} D(t_i)(q_{i-1} - q_i)}{\sum_{i=1}^{N} D(t_i)q(t_i)d_i + \sum_{i=1}^{N} D(t_i)(q_{i-1} - q_i)\frac{d_i}{2}}$$

10.2 Appendix 2: Probit Model Accounting Ratios:

The definitions of the different accounting measures in the Probit Model, taken from Skogsvik 2005:

$$R_1 = return\ onassets = \frac{Earnings\ before\ taxes\ and\ interest\ expense_t}{\left[\frac{Total\ assets_{t-1} + Total\ assets_t}{2}\right]}$$

$$R_2 = Interest\ rate = \frac{Interest\ expense_t}{\left[\frac{Liabilities\ and\ deferred\ taxes_{t-1} + Liabilties\ and\ deferred\ taxes_t}{2}\right]}$$

$$R_3 = Inventory\ turnover = \frac{\left[\frac{Inventory_{t-1} + Inventory_t}{2}\right]}{Sales_t}$$

$$R_4 = Shareholder\ equity\ ratio = \frac{Owner'sequity_t}{Total\ assets_t}$$

$$R_5 = \text{ Change in owners equity} = \frac{(Owner'sequity_t - Owner'sequity_{t-1})}{(Owner'sequity_{t-1})}$$

$$R_6 = diff(R_2) = Normalized\ R_2 = \frac{(R_{2,t} - \bar{R}_{2,t-1})}{\left[\sum_{\tau=t-4}^{t-1} \frac{(R_{2,\tau} - \bar{R}_{2,t-1})^2}{3}\right]^{0.5}}$$

Where:

$$\bar{R}_{2,t-1} = {\sum_{\tau=t-4}^{t-1} R_{2,\tau}}/{4}$$

t = year

Adjusting for choice-based sample bias:

$$\mathrm{P(fail)_{pop}} = \left[1 + \left(\frac{1-\theta}{\theta}\right) \cdot \left(\frac{\mathrm{prop}}{1-\mathrm{prop}}\right) \cdot \left(\frac{1-\mathrm{P(fail)_{est}}}{\mathrm{P(fail)_{est}}}\right)\right]^{-1}$$

where

$$\mathrm{P(fail)_{pop}} = \text{sample based estimate of probability, given prop}$$

$$\mathrm{prop} = \text{proportion of failure companies in the estimation sample}$$

$$\mathrm{P(fail)_{est}} = \text{value of probability assessment in the estimation sample}$$

$$\theta = \text{a priori probability of failure in population of companies}$$

10.3 Appendix 3: Default Probability for Selected Companies

Time period & Default Probabilities

Company					
ABB	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,8560%	0,8560%	0,1540%	0,1540%
	CDS Default	0,6095%	0,3448%	0,2002%	0,3040%
	Probit	0,3933%	0,1795%	0,0478%	0,0087%
Atlas Copco	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,0340%	0,0340%	0,0340%	0,0340%
	CDS Default	0,1677%	0,0975%	0,0794%	0,1827%
	Probit	0,0024%	0,0011%	0,0000%	0,0176%
Electrolux	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,1540%	0,1540%	0,1540%	0,1640%
	CDS Default	0,2521%	0,1790%	0,1213%	0,2828%
	Probit	0,0329%	0,0414%	0,2324%	0,0846%
Ericsson	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,8560%	0,3290%	0,1640%	0,1540%
	CDS Default	0,2639%	0,3040%	0,1117%	0,5419%
	Probit	0,0038%	0,0082%	0,0002%	0,0003%
Sandvik	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,0030%	0,0030%	0,0030%	0,0030%
	CDS Default	0,1283%	0,0862%	0,1074%	0,1074%
	Probit	0,0063%	0,0050%	0,0038%	0,0054%
SCA	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,0340%	0,1540%	0,1540%	0,1540%
	CDS Default	0,1752%	0,1848%	0,0713%	0,2617%
	Probit	0,0080%	0,0165%	0,0040%	0,0035%
Scania	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,0340%	0,0340%	0,0340%	0,0340%
	CDS Default	0,1547%	0,1473%	0,1044%	0,1715%
	Probit	0,0314%	0,0226%	0,0184%	0,0253%
Securitas	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,1640%	0,1640%	0,1640%	0,1640%
	CDS Default	0,2482%	0,2886%	0,0944%	0,2559%
	Probit	0,0392%	0,0230%	0,0535%	0,0842%
SKF	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,0340%	0,0340%	0,0340%	0,0340%
	CDS Default	0,1724%	0,0975%	0,0249%	0,1417%
	Probit	0,0059%	0,0053%	0,0050%	0,0044%
Stora Enso	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,1540%	0,1640%	0,3290%	0,3290%
	CDS Default	0,2406%	0,1925%	0,1867%	1,1533%
	Probit	0,0049%	0,0220%	0,0072%	0,0053%

Time period & Default Probabilities

Swedish Match	**Date**	**2005-01-01**	**2006-01-01**	**2007-01-01**	**2008-01-01**
	S&P	0,0340%	0,0340%	0,1540%	0,1640%
	CDS Default	0,0932%	0,1678%	0,0790%	0,2502%
	Probit	0,0086%	0,0219%	0,0622%	0,1282%
Telia	**Date**	2005-01-01	2006-01-01	2007-01-01	2008-01-01
	S&P	0,0240%	0,0240%	0,0240%	0,0340%
	CDS Default	0,1175%	0,1864%	0,2422%	0,2106%
	Probit	0,0000%	0,0000%	0,0001%	0,0001%
Volvo	**Date**	2005-01-01	2006-01-01	2007-01-01	2008-01-01
	S&P	0,0340%	0,0340%	0,0340%	0,0340%
	CDS Default	0,2050%	0,1082%	0,1324%	0,5359%
	Probit	0,0262%	0,0206%	0,0121%	0,0248%
Vattenfall	**Date**	2005-01-01	2006-01-01	2007-01-01	2008-01-01
	S&P	0,0340%	0,0240%	0,0240%	0,0240%
	CDS Default	0,1361%	0,0970%	0,0578%	0,1864%
	Probit	0,0488%	0,0363%	0,0144%	0,0087%
SAS	**Date**	2005-01-01	2006-01-01	2007-01-01	2008-01-01
	S&P	3,0640%	3,0640%	3,0640%	3,0640%
	CDS Default	0,8820%	1,4100%	1,0986%	2,4485%
	Probit	0,2825%	0,1959%	0,0755%	0,0344%

		ABB	Atlas Copco	Electrolux	Ericsson	Sandvik	SCA	Scania	Securitas
Ratings	2008-01-01	0,154%	0,034%	0,164%	0,154%	0,003%	0,154%	0,034%	0,164%
	2007-01-01	0,154%	0,034%	0,154%	0,164%	0,003%	0,154%	0,034%	0,164%
	2006-01-01	0,856%	0,034%	0,154%	0,329%	0,003%	0,154%	0,034%	0,164%
	2005-01-01	0,856%	0,034%	0,154%	0,856%	0,003%	0,034%	0,034%	0,164%

		SKF	Stora Enso	Swedish Match	Telia Sonera	Volvo	Vattenfall	SAS
Ratings	2008-01-01	0,034%	0,329%	0,164%	0,034%	0,034%	0,024%	3,064%
	2007-01-01	0,034%	0,329%	0,154%	0,024%	0,034%	0,024%	3,064%
	2006-01-01	0,034%	0,164%	0,034%	0,024%	0,034%	0,024%	3,064%
	2005-01-01	0,034%	0,154%	0,034%	0,024%	0,034%	0,034%	3,064%

		ABB	Atlas Copco	Electrolux	Ericsson	Sandvik	SCA	Scania	Securitas
CDS Default	2008-01-01	0,304%	0,183%	0,283%	0,542%	0,107%	0,262%	0,171%	0,256%
	2007-01-01	0,200%	0,079%	0,121%	0,112%	0,107%	0,071%	0,104%	0,094%
	2006-01-01	0,345%	0,098%	0,179%	0,304%	0,086%	0,185%	0,147%	0,289%
	2005-01-01	0,610%	0,168%	0,252%	0,264%	0,128%	0,175%	0,155%	0,248%

		SKF	Stora Enso	Swedish Match	Telia Sonera	Volvo	Vattenfall	SAS
CDS Default	2008-01-01	0,142%	1,153%	0,250%	0,211%	0,536%	0,186%	2,449%
	2007-01-01	0,025%	0,187%	0,079%	0,242%	0,132%	0,058%	1,099%
	2006-01-01	0,098%	0,192%	0,168%	0,186%	0,108%	0,097%	1,410%
	2005-01-01	0,172%	0,241%	0,093%	0,117%	0,205%	0,136%	0,882%

		ABB	Atlas Copco	Electrolux	Ericsson	Sandvik	SCA	Scania
Probit	2008-01-01	0,009%	0,018%	0,085%	0,000%	0,005%	0,003%	0,025%
	2007-01-01	0,048%	0,000%	0,232%	0,000%	0,004%	0,004%	0,018%
	2006-01-01	0,180%	0,001%	0,041%	0,008%	0,005%	0,017%	0,023%
	2005-01-01	0,393%	0,002%	0,033%	0,004%	0,006%	0,008%	0,031%

		Securitas	SKF	Stora Enso	Swedish Match	Telia Sonera	Volvo	Vattenfall	SAS
Probit	2008-01-01	0,084%	0,004%	0,005%	0,128%	0,000%	0,025%	0,009%	0,034%
	2007-01-01	0,053%	0,005%	0,007%	0,062%	0,000%	0,012%	0,014%	0,075%
	2006-01-01	0,023%	0,005%	0,022%	0,022%	0,000%	0,021%	0,036%	0,196%
	2005-01-01	0,039%	0,006%	0,005%	0,009%	0,000%	0,026%	0,049%	0,283%

10.4 Appendix 4: CDS Spreads and Changes

Mid CDS Spread

Date	ABB	Atlas Copco	Electrolux	Ericsson	Sandvik	SCA	Scania
2007-12-31	15,80	9,8	14,7	28,2	5,76	13,6	9,2
2006-12-29	10,4	4,26	6,3	5,8	5,76	3,7	5,6
2005-12-30	20	5,23	9,3	15,8	4,62	9,6	7,9
2004-12-30	35,4	8,998	13,1	15,3	6,88	9,4	8,3

Change in CDS Spread

Date	ABB	Atlas Copco	Electrolux	Ericsson	Sandvik	SCA	Scania
2007-12-31	52%	130%	133%	386%	0%	268%	64%
2006-12-29	-48%	-19%	-32%	-63%	25%	-61%	-29%
2005-12-30	-44%	-42%	-29%	3%	-33%	2%	-5%

Mid CDS Spread

Date	Securitas	SKF	Stora Enso	Swedish Match	Telia Sonera	Volvo	Vattenfall	SAS
2007-12-31	13,3	7,6	60,2	13	11,3	28,8	10	156,4
2006-12-29	4,9	1,337	9,7	4,1	13	7,1	3,1	69,7
2005-12-30	15	5,23	10	9	10	5,8	5,2	89,6
2004-12-30	12,9	9,248	12,5	5	6,3	11	7,3	55,9

Change in CDS Spread

Date	Securitas	SKF	Stora Enso	Swedish Match	Telia Sonera	Volvo	Vattenfall	SAS
2007-12-31	171%	468%	521%	217%	-13%	306%	223%	124%
2006-12-29	-67%	-74%	-3%	-54%	30%	22%	-40%	-22%
2005-12-30	16%	-43%	-20%	80%	59%	-47%	-29%	60%