



LUND UNIVERSITY
School of Economics and Management

NEKN05 MASTER'S ESSAY

Nordic Banks

Credit Risk and Risk Linkages

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Abstract:

The recent global financial crisis has once again shown how fragile the financial system is. This essay investigates the credit risk in the Nordic banking sector by measuring the probability of default of the six major Nordic banks. This is done by using the Merton (1974) model which utilizes stock prices as well as balance sheet data. The results are compared with an approach first suggested by Hall and Miles (1990) which relies solely on stock market prices. In order to highlight the risk of a highly concentrated banking sector, the essay also investigates the spillover effects from one bank to another. The essay follows the example of Adrian and Brunnermeier (2011) that have developed the commonly used VaR into CoVaR, a risk measure that takes systemic risk into account.

Keywords: banking crisis; probability of default; Merton; Hall and Miles; VaR; CoVaR

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1. Introduction

Banks and other financial institutions are an important part of the foundation of a well-functioning modern economy. Still, the global financial crisis proved that these institutions are particularly vulnerable and exposed to contagiousness. Economic crises are often the result of complex circumstances, however for the global financial crisis it is safe to say that the credit risk of financial institutions played a key role.

The overall aim of this essay is to investigate the health of the largest Nordic banks. This will be done by examining their credit risks and risk linkages. While the whole Nordic banking sector may be considered as relatively stable, the Swedes can still recall when Swedbank almost collapsed in 2008. Also, both Norway and Sweden experienced severe banking crises in the beginning of the 1990's. This record of instability and the structure of the Nordic banking sector with a few, all connected, large players are the motivations for this essay. But in fact, the natural structure of low equity compared to leverage ratio makes all banks important to monitor closely.

The first part of this essay investigates the individual credit risks of the largest Nordic commercial banks by first using the cornerstone of the structural models of credit risk; the Merton model developed by Robert C. Merton (1974). The model is used to evaluate the credit risk of a company's debt. Simplified, the model accounts for when a failure will occur by looking at the value of a company's assets compared to its liabilities. The likelihood of this failure, commonly referred to as the probability of default, is based on the assets and the capital structure of a company. While the essay will rely on the structural approach for assessing credit risk, we control and compare our results from the Merton model by also calculating the probability of default with a model originally suggested by Hall and Miles (1990). This approach was developed and applied to banks specifically and relies solely on market information. We include 2005Q1-2013Q4 in our calculations to cover the periods pre-, during and post the global financial crisis. Our aim of this part is to, in terms of probability of default, demonstrate how the banks performed during these periods. The results will show how each bank was affected during distress and also look at the more recent performance in order to obtain an indication of the banks' more current health status.

The second and last part of the essay serves as a complement to the first part and investigates the risk linkages between the same largest Nordic commercial banks. The structure of a banking sector is often heavily interlinked and the Nordic sector is not an exception. As a matter of fact, according to the “Nordic regional report” (2013) from the International Monetary Fund, the strong linkages between the Nordic banks is one of the most concerning weaknesses of the Nordic banking sector. To investigate these risk linkages we have chosen a model for systemic risk developed by Adrian and Brunnermeier (2011). They suggest a measure called CoVaR, an extension of the widely used risk measure value at risk which they use to assess the risk contribution from U.S financial institutions to the system. In order to be able to investigate the above mentioned weakness of the Nordic banking sector, we will use CoVaR in a slightly modified way and look at the risk contribution from one bank to another. Also this model is based on market information. Our aim with this part of the essay is to complement the first part - We aim to give a fuller picture of the formerly and current health status of the individual banks by searching for differences in vulnerability in terms of risk linkages.

We believe our contribution with this essay is the attempt to give a fuller picture of the health of the individual banks. The most obvious limitation of this essay is that it does not explain the underlying mechanisms of the results of credit risk and risk linkages. Also, there is evidently criticism against the used models which we will account for below and we will critically review our results. For instance, Vassalou and Xing (2008) propose that the probability of default should not be interpreted literally and this limits the results to only reflect a relative ranking. With regards to our attempt to contribute with a fuller picture of the health status, we are limited by the fact that the models for credit risk are not combinable with the model for risk linkages. Thus we are not able to provide a combined measure for each bank, which would have given a more comprehensive picture.

The remainder of this essay is organized as follows; section 2 briefly summarizes the Nordic banking sector and its vulnerabilities, section 3 presents relevant literature on credit risk, section 4 is the method section reviewing the used credit risk models, section 5 clarifies the data used and section 6 presents the result. With section 7 the second part of the essay begins with a literature review on systemic risk, section 8 explains the chosen method and section 9 and 10 presents data and result, respectively. Lastly, section 11 summarizes and concludes both parts of the essay.

CREDIT RISK

2. The Nordic banking system and its vulnerabilities

This section will give an overview of the structure of the Nordic banking sector, present the banks included in our calculations and also establish a sense of what weaknesses that may threaten the stability of the sector. The following is a very brief and simplified version of the banks' structures as these are very complex.

What characterizes the Nordic banking market is the predominance of a small number of relatively large banks. These banks are Nordea, Swedbank, Handelsbanken, Skandinaviska Enskilda Banken (SEB), Danske Bank and DNB. The four first mentioned banks have their headquarters in Sweden and the other two in Denmark and Norway respectively. Furthermore, in addition to the relative size of these six financial institutions compared to their competitors, they are in most cases also large relative to GDP. In "Nordic Regional Report" (2013) the International Monetary Fund has analyzed the banks' balance sheets and found that these six banks account for 90 percent of the assets of all publicly listed Nordic banks and that the size of their assets are worth 185 percent of the Nordic GDP. In addition, the largest banks in each home country, Nordea, DNB and Danske Bank represent 30 percent of the Nordic GDP.

According to the report "The Swedish Financial Market" (2013) from Sveriges Riksbank, the four Swedish banks have almost half of its lending to customers abroad. As a major player also outside its home market, Nordea has 75% of its lending outside Sweden but mainly to Nordic customers. The other three banks have their largest lending within Sweden with on average a quarter to the other Nordic countries. A notable part of Swedbank's and SEB's lending is devoted to the Baltic countries. SEB is also growing in Germany while Handelsbanken is currently taking market share in United Kingdom. In Norway, Norges Bank reports in "Financial Stability Report" (2013) that the largest Norwegian bank, DNB, accounts for 30 percent of the total lending in Norway and the bank operates mainly on its home market. In the full rating report "Danske Bank AS" (December 2013) from Fitch Ratings, it is stated that Danske Bank is

Denmark's leading bank with 30% of the Danish deposits and lending and has 5-10% of the market share in the other Nordic countries. The bank also operates in the Baltics and Ireland.

All banks except DNB and Handelsbanken have expanded in the Baltic countries, and according to the "Annual Report" (2013) from Swedbank, their dominance is most notable in Estonia where they together control around 90 percent of the market. Swedbank is the bank with the largest customer base in the Baltics. With 4,0 million customers in Estonia, Latvia and Lithuania combined, the Baltic customer base is as large as the original home market of Sweden, with 4,1 million customers. In "Myndigheternas insatser för finansiell stabilitet" (2011), Riksrevisionen reports that in 2007, the operations in the Baltics made up almost a third of the EBIT of Swedbank and almost a fifth of SEB. For Nordea, the proportion rose to 3 percent at the most, in 2008. The report also concludes that the banks increased their risk exposure by expanding in the Baltic countries. The Baltic economies grew uncontrollably and as a result they faced growing imbalances. For instance, the credit expansion was extreme with increased lending volumes of 40-70 percent a year during 2005-2007 in these countries.

The Nordic banks are as all banks sensitive to exogenous shocks. In the "Nordic Region Report" (2013), IMF summarizes that for the Nordic region, the indebted households together with the increasing prices on the housing market compose a challenge for the stability. However, due to the "deeply integrated banking system" (p. 11), the banks within the region are especially vulnerable because of the imminent risk of transmission. The banks have widespread cross-border operations and IMF suggests that they "operate more as regional banks rather than national banks" (p. 11). Hence, the interlinkages caused by the banks operating regionally, threatens to intensify eventual shocks. Regulations such as the Basel regulation with equity capital requirement, are mainly focused on the individual bank. However, Elsinger et al. (2006) warn that focusing on bank stability on an individual level is not sufficient in the event of an extreme shock as correlations in bank portfolios and credit interlinkages can alter the shock and cause a domino effect. Specifically for the Nordics, Blåvarg and Nimander (2002) advise that in a concentrated systems as the Nordic banking system, one can expect a more concentrated interbank market with stronger credit interlinkages and undiversified risk.

In the “Financial Stability Report” (2013) from Norges Bank, it is reported that The Nordic loan-to-deposit ratios are twice as high as the average of European banks and IMF reports in the “Nordic Regional Report” (2013) that for example Danske Bank and Swedbank are looking at LTD ratios of 220 percent. To fund the great banking sector, there is a need to turn to external funding; the banks rely extensively on wholesale funding. As widely argued, and especially after the global financial crisis and the fall of Lehman Brothers, a heavy reliance on wholesale funding increases the vulnerability of a bank.

3. Literature review - Credit risk

Robert C. Merton’s paper “On the pricing of Corporate Debt: The Risk Structure of Interest Rates” (1974) extended the Black-Scholes model (1973) and presented a model for evaluating the credit risk of a company. With the model being based on a new theory, it became the foundation of a new class of models for credit risks; the structural, or asset value models. Other literature on credit risk is for example based on static models such as accounting models. However, this kind of models has been criticized by for example Vassalou and Xing (2004) as backward looking as they do not reflect market expectations. Byström (2003) also criticizes possible accounting manipulations and the obvious time lag. The Merton model assumes that a firm’s debt can be seen as a zero-coupon bond that matures at time T and if the assets at this time T are less than the debt, the firm will default. The inputs needed for the model are the asset value, its volatility and the debt of a company – A higher standard deviation of the asset value fluctuations contributes to a higher likelihood of default and an increase on capital to debt ratio contributes to a lower likelihood of default. To clarify, for a bank, the debt can be thought of as mainly deposits.

The Merton model has been extensively used for examining the credit risk for companies but it has also been extended and modified in numerous ways. Tudela and Young (2005) refer to the extended models that for example add other financial data to original Merton approach as “hybrid approaches”. One of the most widely known hybrid approaches is the commercial KMV’s default risk model, which framework is summarized by Crosbie and Bohn (2002). While it relies on the Merton model’s structure of forecasting the probability of default it distinguish itself by applying an empirical distribution of U.S companies’ defaults on the asset value fluctuations instead of the originally assumed normal distribution. Also other parts of the model are refined. For instance,

debt is defined as all short-term liabilities plus half the book value of all long term debts and the standard deviation of the asset returns is estimated from historical data but also through an applied iterative procedure. Tudela and Young (2005) show that the Merton model provides useful and reliable information. They apply the model to UK public companies and with different techniques such as comparing the results to actual default records, other default models and various statistical measures including power curves and accuracy ratios, they find that the default probability obtained from using the Merton model is a “strong signal of failure one year in advance of its occurrence”.

Credit risk models are mainly used by financial institutions and investors to evaluate the credit risk of a company. However, alike in this essay, they may also be applied to investigate the health of a financial institution itself. Allen and Powell (2010) use the Merton model along with other measures such as VaR to investigate the default probability of Australian banks before and during the global financial crisis. They find that while a raised ranking of the major Australian banks was somewhat accurate relative to their peers, all the banks did experience a significant increase in the probability of default during the financial crisis.

Byström (2003) finds that the financial institutions’ “high leverage ratio and opaque balance sheets” (p. 2) may affect the results from the Merton model to be misleading. In other words, the probability of default produced in the Merton model will be less sensitive to a change in the leverage ratio for a highly leveraged company such as a bank. In addition to this sector specific issue, the author also problematizes the fact that the extended KMV model has substituted the assumed normal distribution with a non-public database of default statistics and therefore the model cannot be used by the broad public to assess credit risk with the same accuracy. To investigate the Swedish banks’ performance during the 90’s crisis he instead relies on a structural, purely market based approach developed by Hall and Miles (1990). The author compares his results with one of the most known credit rating agencies and concludes that even if it is problematic to estimate the preciseness of default probabilities, they surely seem to capture and evaluate changes faster and to a wider extent than the credit ratings. With this market based approach Hall and Miles (1990) aimed to develop a new technique for assessing the credit risk of institutions’ portfolios. The model is based on ”share prices with time varying risk premia to

analyze market perceptions of volatility” (p.1) and looks at the measure $1/\sigma_{\varepsilon_t}$ in order to assess a probability of default to a financial institution. As Clare and Priestly (2002) mentions, while the measure may be compared to those developed by Santomero and Vinso (1977) and Hannan and Hanweck (1988), it is unique in its way that it gives a forecasting measure by employing stock prices. With forward looking default probabilities one is given indications of where intervention or change in regulation may be needed. Hall and Miles (1990) themselves applied their method to four at the time relatively stable UK banks. With the aim to develop a technique for forecasting default probability the validity of the method was rather difficult to estimate when no banks were in trouble. In addition to Byström (2003) confirming the method, Clare and Priestly (2002) apply the method on the Norwegian banking sector during the Norwegian banking crisis in the early 90’s. Thus, these “favorable” circumstances should better indicate of the properties of the risk measure. The authors find that the stock market forecasted the crisis well before (over a year) the crisis has been agreed to have begun at the earliest.

4. Method

4.1 Merton approach

The Merton model was developed to evaluate the credit risk of a company’s debt. Simplified, the model measures the probability of default by combining the market asset’s volatility with asset and debt levels. The firm is assumed to default when the asset value falls below the value of the debt.

The first step towards determining the default probability is to identify the probability distribution of the assets at the time of the maturing, time T. We will, as the original Merton model, assume that the logarithm of the asset value is normally distributed. The yearly log variance of the asset value changes by σ^2 and the expected yearly change of the asset value is denoted by $\mu - \sigma^2/2$ where μ is a drift parameter. With this established and normal distribution assumed, the log asset value in T can be denoted as follows:

$$\ln A_t \sim N \left((\ln A_t + (\mu - \sigma^2/2)(T - t)), \sigma^2(T - t) \right) \quad (1)$$

Theoretically, if we knew L (liabilities), A_t , μ and σ^2 estimating the default probability would only be a matter of statistics where the probability of default could be calculated as follows:

$$\begin{aligned} Prob(Default) &= \Phi \left[\frac{\ln L - \ln A_t - (\mu - \sigma^2/2)(T - t)}{\sigma\sqrt{T - t}} \right] \\ &= \Phi \left[\frac{\ln(L/A_t) - (\mu - \sigma^2/2)(T - t)}{\sigma\sqrt{T - t}} \right] \end{aligned} \quad (2)$$

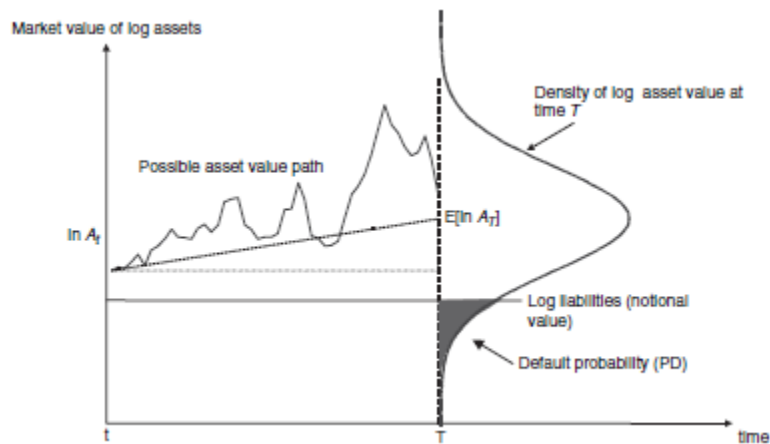
where Φ denotes the cumulative standard normal distribution.

To clarify one step further, we are measuring how many standard deviations away from default A_t is. This measure is often referred to as distance to default in credit risk literature and is denoted by;

$$\begin{aligned} DD &= \frac{\ln A_t + (\mu - \sigma^2/2)(T - t) - \ln L}{\sigma\sqrt{T - t}} \\ \Rightarrow Prob(Default) &= \Phi[-DD] \end{aligned} \quad (3)$$

The below figure from “Credit risk modelling using Excel and VBA” (Löffler and Posch, Wiley Finance (2007), p. 29) demonstrates the above explained idea of the Merton model.

Figure 1: The Merton Model

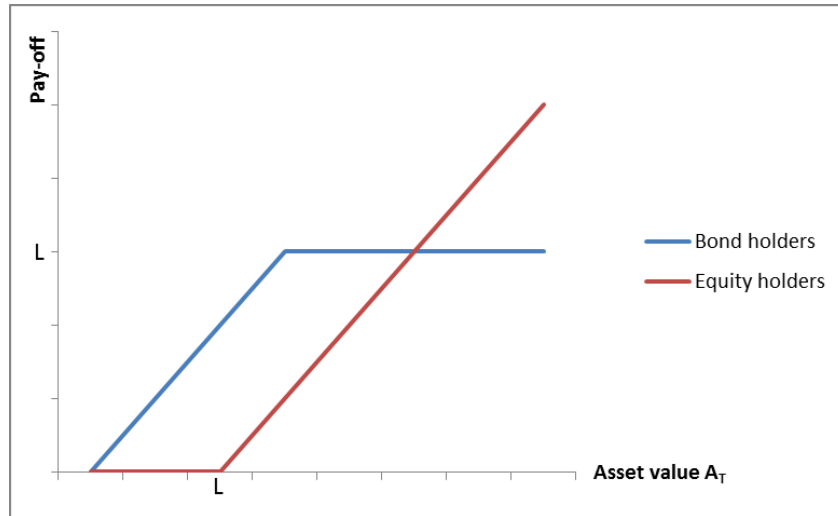


As we have indicated above, to apply the Merton model on a real company, it takes more than basic statistics. This is due to the fact that we cannot observe the market value of the firm's assets, meaning that we do not know A_t and consequently, neither its volatility. From the firm's balance sheet we can observe the book value of the assets but this may differ from the market value for many reasons. Merton chose to apply option pricing theory in order to establish a relationship between the two (related) unobservable variables and the observable ones. Note that this demands a publicly traded firm as we start by observing the market value of equity which is the share price multiplied with the number of outstanding shares. We have already assumed the value of the liabilities at time T (by assuming consistent maturity structure) and we can also assume that in the event of default, the bondholders will claim the assets and equity is zero (note that this would be done at time T). However, under ordinary circumstances where the asset value is above the value of the liabilities, the equity holders get the residual value. This can be demonstrated as they pay-off for a European call option:

$$E_t = \max(0, A_t - L)$$

The pay-off follows that of a European call option on the underlying assets of the bank A_t and the liabilities L representing the strike price. For bondholders, the pay-off mimics that of a portfolio consisting of a risk-free zero coupon bond valued at L together with a short put on the assets with strike price L .

Graph 1: European call option



Assuming that no dividends are paid out, the equity at t can be determined with the Black-Scholes call option formula (1973).

$$E_t = A_t \cdot \Phi(d_1) - Le^{-r(T-t)}\Phi(d_2) \quad (4)$$

where

$$d_1 = \frac{\ln(A_t/L) + (r + \sigma^2/2)(T - t)}{\sigma\sqrt{T - t}} \quad (5)$$

and

$$d_2 = d_1 - \sigma\sqrt{T - t} \quad (6)$$

r denotes the risk free interest rate.

If we then rearrange the formula to free the market asset value A_t , we get

$$A_t = [E_t + L_t e^{-rt(T-t)}(d_2)] / (d_1) \quad (7)$$

for “today’s” asset value and by doing this for all trading days in a year we can get a system of equations. Assuming the one year maturity (i.e setting (T-t) to 1), the system will look as follows;

$$\begin{aligned} A_t &= [E_t + L_t e^{-rt(T-t)}(d_2)] / (d_1) \\ A_{t-1} &= [E_{t-1} + L_{t-1} e^{-rt-1}(d_2)] / (d_1) \\ &\dots \\ A_{t-260} &= [E_{t-260} + L_{t-260} e^{-rt-260}(d_2)] / (d_1) \end{aligned} \quad (8)$$

We do have two unknown variables, however the volatility can be estimated with the help of a time series of A.

With A and its volatility found by help of the system above only one variable is left to find, the drift rate. The drift parameter is determined using CAPM (9). By regressing the asset values returns on the OMX index return we obtain β , the sensitivity of the asset return compared to the market portfolio return. We assume a market risk premium rate of 4% and estimate the expected return of the asset. By taking the logarithm of $(1+E(r_i))$, the drift rate is obtained.

$$E(r_i) = r_f + \beta_{im}(E(r_m) - r_f) \quad (9)$$

We now have all the variables to calculate distance to default which we by the cumulative standard normal distribution turn into a probability measure,

$$DD = \frac{\ln A_t + (\mu - \sigma^2/2)(T - t) - \ln L}{\sigma\sqrt{T - t}}$$

$$\Rightarrow Prob(Default) = \Phi[-DD]$$

4.2 The Hall and Miles market based approach

The Hall and Miles market based approach is based on the idea of solely relying on the market's ability of evaluating a firm's balance sheet, thus its portfolio of assets and liabilities. Needless to say, an expected brighter future of a firm will be reflected in an increase in stock prices and a decrease in probability of default. This market based approach is using the capital asset pricing model (CAPM) in order to derive the distance to default through stock price volatility. In summary the approach assumes market efficiency and that CAPM is able to capture the risk return relationship. As market efficiency is assumed, the variability of the market expectations reflects the variability in a firm's assets and liabilities. As in all structural credit risk approaches, the company defaults when liabilities are greater than assets. Hence we can use the variability (explained below) to derive a simple metric for determining the probability of default.

To start with, the basic assumption made is an efficiently determined share price

$$S_{it} = \frac{\sum_{j=1}^n P_{jt} X_{jt}}{N} \quad (10)$$

Where S_{it} is the price of stock i at time t , P_{jt} is the price of stock i 's assets/liability, X_{jt} is asset/liability and N is the number of shares.

As mentioned above, the measure of the default probability is based on a conditional version of CAPM. As per CAPM, the expected return at time t , $E(R_t)$ for an individual stock can be divided into the risk free return at time t , RF_t and the (time varying) risk premium RP_t .

$$E(R_t) = \frac{E(S_t - S_{t-1})}{S_{t-1}} = RF_t + RP_t \quad (11)$$

where the risk premium can be further expanded to

$$R_t = RF_t + \lambda_t E(ND_t) + \varepsilon_t \quad (12)$$

where λ_t is the market price of risk and $E(ND_t)$ is the amount of expected non-diversifiable risk. As CAPM is only true on average a stochastic error term is added at the end, making the above expression to show the actual return (i.e. not the expected).

We are now ready to express the actual bank capital;

$$S_t N = S_{t-1} N \{1 + RF_t + \lambda_t E(ND_t) + \varepsilon_t\} \quad (13)$$

As the right side of the above expression shows, the bank capital is the value of all outstanding shares as share price is assumed to efficiently reflect the balance sheet. The value of the bank capital is determined by

$$(S_{t-1} N)^2 \sigma_{\varepsilon_t}^2 \quad (14)$$

where $\sigma_{\varepsilon_t}^2$ represents the variance in the market value of the underlying asset, the bank, around the expected market value. Assuming the market effectivity holds, we can by dividing the value of the asset $S_{t-1} N$ with its standard deviation $S_{t-1} N \sigma_{\varepsilon_t}$ obtain a value representing the number of standard deviations of the value of the bank; a measure of the distance to default.

$$\frac{S_{t-1} N}{S_{t-1} N \sigma_{\varepsilon_t}} = \frac{1}{\sigma_{\varepsilon_t}} \quad (15)$$

This value can then be transformed into a probability of default. For example, a measure $1/\sigma_{\varepsilon_t} = 2,33$ indicates at 1 in 100 probably of default whilst a value of 3,09 indicates a 1 in 1000 probability. Since this gives us the distance to default, an increase in the standard deviation means a lower value of the quota, indicating a short distance to default and in return a higher probability of default.

In order to find σ_{ε_t} we continue by rewriting formula (11), which according to CAPM can be written as

$$E(R_t) = \frac{E(S_t - S_{t-1})}{S_{t-1}} = RF_t + \beta_t E(RM_t - RF_t) \quad (16)$$

where RM_t is the return on the market portfolio, OMX N40 in our case and β is defined as the expected covariance between the return of the individual stock and the expected return of the market portfolio divided by the expected variance of the return on the market portfolio:

$$\frac{E(\sigma_{R_t, RM_t})}{E(\sigma_{RM_t}^2)} \quad (17)$$

Further on, according to CAPM, the risk premium on the market portfolio is the market price of risk, λ_t , multiplied by the expected variance $E(\sigma_{RM_t}^2)$ of the market portfolio returns. The market price of risk, λ_t is defined as the expected excess return on the market portfolio over the risk-rate divided by the expected variance on the market portfolio.

$$\lambda_t = \frac{E(RM_t - RF_t)}{E(\sigma_{RM_t}^2)} \quad (18)$$

This gives us

$$E(RM_t) = RF_t + \lambda_t E(\sigma_{RM_t}^2) \quad (19)$$

Formula (12) is adapted from the stock to the market portfolio, giving

$$RM_t = RF_t + \lambda_t E(\sigma_{RM_t}^2) + v_t = RF_t + \lambda_t E(\sigma_{v_t}^2) + v_t \quad (20)$$

which on average is correct plus an error term, v_t , that is zero on average.

We continue by adding the error term ε_t to formula (16) while replacing β with its definition.

$$R_t = RF_t + \frac{E(\sigma_{R_t, RM_t})E(RM_t - RF_t)}{E(\sigma_{RM_t}^2)} + \varepsilon_t \quad (21)$$

and using the definition of the market price of risk

$$R_t = RF_t + \lambda_t E(\sigma_{R_t, RM_t}) + \varepsilon_t = RF_t + \lambda_t E(\sigma_{\varepsilon_t, v_t}) + \varepsilon_t \quad (22)$$

To finally obtain our distance to default measures, it is necessary to model the variances and covariances from (20) and (22). In three previous papers, the authors Hall and Miles (1990), Claire and Priestly (2002) and Byström (2003) have all chosen different variations of ARCH to model these variances and covariances. Hall and Miles chose restricted versions of ARCH and GARCH. Claire and Priestley used a non-standard AGARCH-M bivariate model. Byström argued “when estimating a multivariate GARCH-M system one easily ends up with tens (or hundreds) of parameters to estimate. In order to keep the number of parameters down, and hopefully get more reasonable parameter estimates, one should therefore favor parsimonious representations to more elaborated ones” (p. 11). We have therefore chosen to follow Byström’s example of a GARCH(1,1) representation overlooking potential asymmetries or seasonality, rather than the representations of Hall and Miles and Claire and Priestley. In order to narrow down the parameters necessary to estimate, a constant market price of risk and a constant correlation for the covariance matrix are assumed.

Using GARCH(1,1) refers to the use of the most recent observation of u^2 and the most recent estimate of σ^2 – we calculate the variance rate, σ_n^2 on the market portfolio according to the following formula:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (23)$$

where V_L is the long-run average variance rate and u_i is the continuously compounded return,

$$u_i = \ln \frac{S_t}{S_{t-1}} \quad (24)$$

and γ , α and β are weights assigned to the different parameters where

$$\gamma + \alpha + \beta = 1.$$

To be able to calculate γ we set $\omega = \gamma V_L$ which gives us the model

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \quad (25)$$

By estimating the parameters ω , α and β , we are then able to obtain γ as $1 - \alpha - \beta$ and V_L as $\frac{\omega}{\gamma}$.

To estimate the true parameters necessary for the GARCH(1,1) model we start by giving the parameters random weights. To obtain the correct values we continue by using the maximum likelihood approach. The problem consists of estimating the variance of a variable, X , with u_1, u_2, \dots, u_m number of normally distributed observations. The variance estimated for day i , σ_i^2 is defined as v_i . The probability of u_i being observed is given by the probability density function of $X = u_i$.

$$\prod_{i=1}^m \left[\frac{1}{\sqrt{2\pi v_i}} \exp\left(\frac{-u_i^2}{2v_i}\right) \right] \quad (26)$$

and by taking the logarithms we have the expression

$$\sum_{i=1}^m \left[-\ln(v_i) - \frac{u_i^2}{v_i} \right] \quad (27)$$

This expression is then maximized by adjusting the parameters ω , α and β ¹. With these parameters estimated, we are able to proceed to estimate the following parameters:

¹ Parameters are shown in the results section.

$$\begin{aligned}
R_t - RF_t &= \alpha_{i,1} + \lambda E(\sigma_{\varepsilon_t, v_t}) + \varepsilon_t \\
RM_t - RF_t &= \alpha_{m,1} + \lambda E(\sigma_{v_t}^2) + v_t
\end{aligned}
\tag{28}$$

$$\begin{aligned}
E(\sigma_{\varepsilon_t}^2) &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{\varepsilon_{t-1}}^2 \\
E(\sigma_{v_t}^2) &= \omega + \alpha v_{t-1}^2 + \beta \sigma_{v_{t-1}}^2 \\
E(\sigma_{\varepsilon_t, v_t}) &= \rho_{\varepsilon, v} \sqrt{E(\sigma_{v_t}^2) E(\sigma_{\varepsilon_t}^2)}
\end{aligned}
\tag{29}$$

where $E(\sigma_{\varepsilon_t}^2)$ and $E(\sigma_{v_t}^2)$ are the expected conditional variances, $\rho_{\varepsilon, v}$ is the correlation coefficient between ε and v and $E(\sigma_{\varepsilon_t, v_t})$ represents the expected covariance between ε_t and v_t . $\varepsilon_t = \sigma_{\varepsilon_t} u_1$ and $v_t = \sigma_{v_t} u_2$ where $u_i \sim N(0,1)$ – ultimately ending up with our distance to default coefficient σ_{ε_t} .

In order to match the results from the Hall and Miles market based approach with the Merton approach, a view of quarterly data with probability of default within one year is chosen. This is achieved this by multiplying the sum of the daily σ_{ε_t} for each quarter with the square root of four.

5. Data

5.1 Shares

We obtain daily share prices of the six major Scandinavian banks (Danske Bank, DNB, Handelsbanken, Nordea, SEB and Swedbank) from Datastream. The data is collected over the time period 2005Q1-2013Q4.

5.2 Balance sheet data

Quarterly data of the banks liabilities and outstanding shares are collected from the banks respective balance sheet data. The market value of equity of the banks is calculated by taking the daily share price times the average number of outstanding shares for that quarter. The quarterly figures of the liabilities are connected with the daily figure of market value of equity by taking the liabilities as it was known in that time period, i.e. the data of liabilities for Q1 is available for use in Q2. The liabilities of Q1 are connected with the market value of equity of Q2.

5.3 Risk-free rate

To simulate the risk-free rate of return, the 12 month Interbank Offered Rates for Sweden, Norway and Denmark are collected². STIBOR, NIBOR, CIBOR respectively; Stockholm, Norway and Copenhagen Interbank Offered Rate. The IBOR rates are obtained from the Swedish and Norwegian national banks and Datastream for the CIBOR.

5.4 Market portfolio

To represent the market portfolio in CAPM, the OMX N40 stock market index is used. The OMX N40 is a capitalization-weighted stock market index administered by the Nasdaq OMX Group. It consists of the 40 most traded stocks on the Nordic markets operated by the Nasdaq OMX Group - Stockholm, Copenhagen, Helsinki and Reykjavik. Nasdaq OMX does not operate on the Norwegian market, hence no Norwegian stocks are included. No Icelandic stocks are currently included in the index (February 2015). Prominent companies in the index are ABB, Hennes & Mauritz, Volvo Group, Novo Nordisk with Nokia having the largest weight (February 2015) as well as five of the major Nordic banks (DNB not included). Since the essay is focused on Scandinavian banks, a market portfolio consisting of Scandinavian or Nordic companies is appropriate. Other indices such as the S&P500 could also have been used although the writers deemed a local market portfolio more relevant.

² As of 2013-03-04 the STIBOR 12M was not available and the STIBOR 6M was used instead.

6. Results

Below is the summary statistics of the daily returns between 2005Q1 and 2013Q4. From the standard deviation we can tell that SEB and Swedbank had the highest volatility during this period while Handelsbanken had the lowest. DNB and Handelsbanken had the highest average return while Danske Bank experienced a negative, even if close to zero, average return. In line with the volatility measure, SEB followed by Swedbank had the highest, and lowest, observed returns. From table 2 we can clearly see that that the banks were affected by the global financial crisis. A common denominator for all six is that their share prices all dropped to their lowest in 2009, after the crisis hit. Worst hit was Swedbank with a remaining value of a mere 6,5% of that before the crisis, just two years after its maximum.

Looking at table 1 again, the skewness measures of the returns show that Danske Bank, DNB and Swedbank had a negatively skewed distribution. This means that the probability distribution of the returns has an asymmetric tail extended towards the left. The distribution of returns of Nordea, Handelsbanken and SEB were positively skewed, especially the distribution for Nordea. A skewness measure equal to zero implies normal distribution. Hence, the returns are not normally distributed. Also from the kurtosis we can tell that the returns are not normally distributed. A value higher than 3 indicates a higher peak than a normal distribution. In addition to the below tables, appendix 1 contains graphs of the asset returns and appendix 2 shows the yearly volatility for each bank.

Table 1: Summary statistics for 2005Q1-2013Q4. Number of observations: 2346.

	Mean	Standard Dev	Kurtosis	Skewness	Minimum	Maximum
DANSKE BANK	-0.0000378	0.0221782	5.7416574	-0.0865960	-0.1718299	0.1396680
DNB	0.0002737	0.0257747	9.8601086	-0.1190277	-0.2050746	0.2109305
HANDELSBANKEN	0.0002709	0.0195696	6.4833310	0.1643223	-0.1073993	0.1328609
NORDEA	0.0002195	0.0215593	6.2748332	0.5284164	-0.1203243	0.1491267
SEB	0.0001214	0.0272053	11.3012416	0.0539497	-0.2232196	0.2321481
SWEDBANK	0.0001124	0.0269092	7.8025816	-0.1989435	-0.2053768	0.1735784
OMX	0.0003267	0.0151998	5.0313021	-0.1288646	-0.0834942	0.0982940

Table 2: Highest and lowest observed share price for 2005Q1-2013Q4. The currencies for the prices are DKK for Danske Bank, NOK for DNB, SEK for Handelsbanken, Nordea, SEB, Swedbank and EUR for OMX.

	DANSKE BANK	DNB	HANDELSBANKEN	NORDEA	SEB	SWEDBANK	OMX
Max	256.62	109.9	317.3	93.67	128.2	233.26	1441.46
Date	19.02.2007	28.11.2013	27.12.2013	26.04.2007	20.04.2007	15.02.2007	10.11.2007
Min	31	15.86	85.5	32.07	15.99	15.22	500.4
Date	06.03.2009	20.01.2009	02.02.2009	23.01.2009	03.03.2009	06.03.2009	06.03.2009

In the following tables and charts an extract of the probabilities of default are provided. In order to narrow down the results, the full period is not shown in the tables but can be found in appendix 3 together with the distance to default measures in appendix 4. Distance to default and probability to default are inversely related. The shorter the distance to default, which indicates the number of standard deviations around the expected value of the bank, the higher the probability of default.

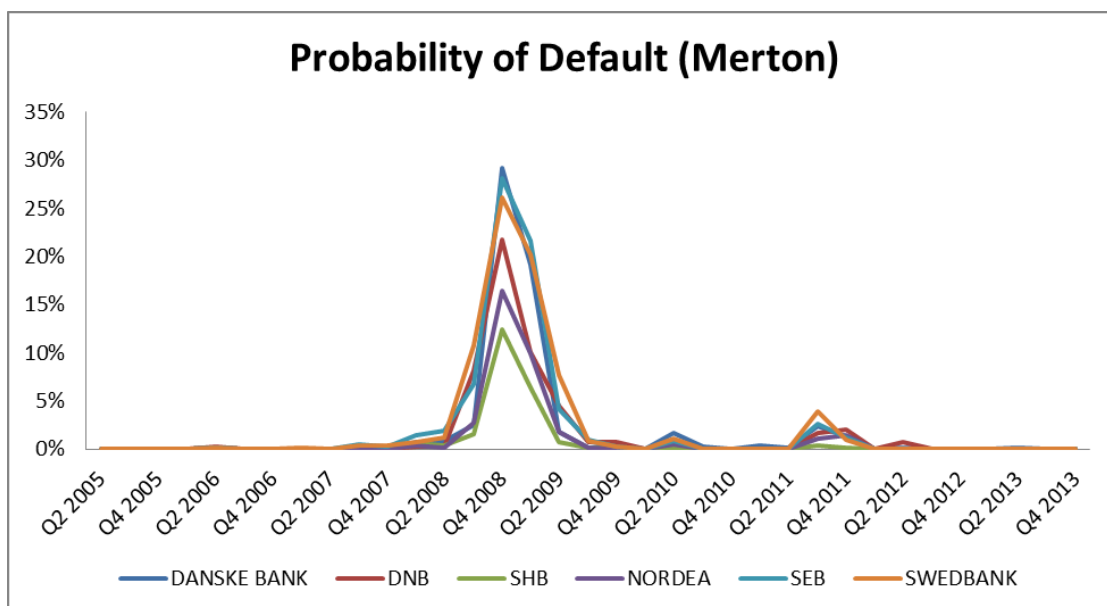
Table 3: Summary of the one year probabilities of default results using the Merton model

MERTON	DANSKE BANK	DNB	SHB	NORDEA	SEB	SWEDBANK
Q4 2007	<0,01%	<0,01%	<0,01%	<0,01%	0,242%	0,315%
Q1 2008	0,713%	0,233%	0,612%	0,315%	1,468%	0,735%
Q2 2008	0,854%	0,254%	0,421%	0,127%	1,915%	1,212%
Q3 2008	2,517%	8,150%	1,503%	2,681%	6,684%	10,713%
Q4 2008	29,144%	21,709%	12,356%	16,420%	28,163%	26,142%
Q1 2009	19,092%	10,098%	6,432%	9,877%	21,640%	20,234%
Q2 2009	1,774%	4,459%	0,701%	1,782%	4,191%	7,645%
Q3 2009	0,095%	0,720%	0,136%	0,116%	0,898%	0,885%
Q4 2009	0,436%	0,727%	<0,01%	0,052%	0,224%	0,189%
Q1 2010	<0,01%	0,030%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2010	1,667%	0,168%	0,018%	0,489%	0,782%	1,061%
Q3 2010	0,211%	0,042%	<0,01%	0,015%	0,011%	<0,01%
Q4 2010	0,014%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2011	0,306%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2011	0,096%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2011	2,374%	1,657%	0,331%	1,095%	2,655%	3,946%
Q4 2011	1,343%	1,968%	0,139%	1,453%	1,231%	0,947%
Q1 2012	0,064%	0,050%	<0,01%	<0,01%	0,022%	0,018%
Q2 2012	0,128%	0,732%	<0,01%	0,059%	0,052%	0,018%
Q3 2012	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2012	0,025%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	0,039%
Q2 2013	0,086%	0,023%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2013	0,013%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%

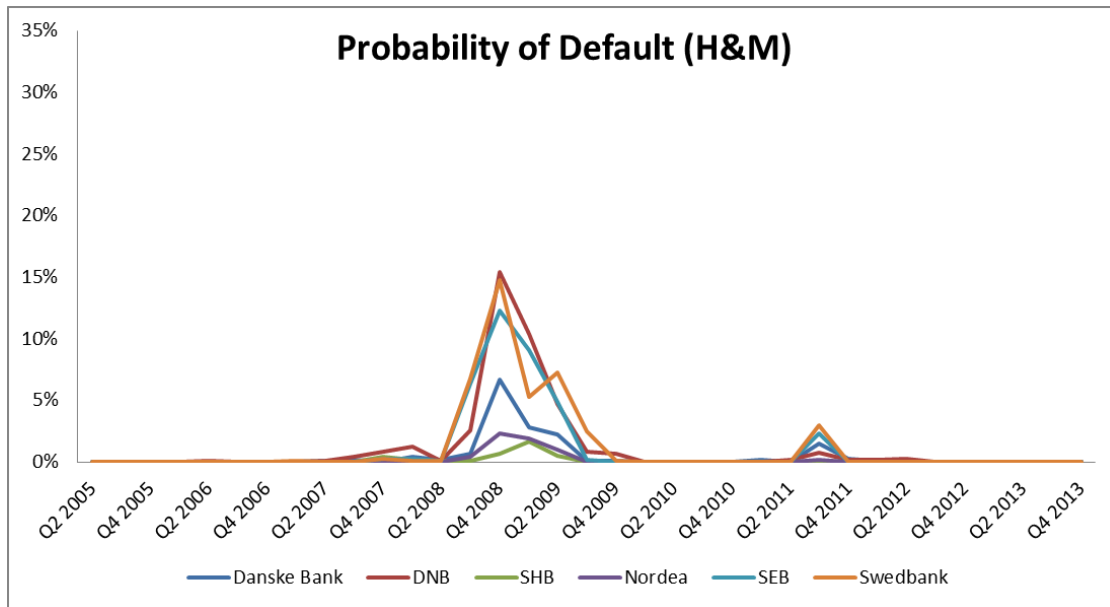
Table 4: Summary of the one year probabilities of default results using the Hall and Miles approach

HALL & MILES	DANSKE BANK	DNB	SHB	NORDEA	SEB	SWEDBANK
Q4 2007	0,037%	0,828%	0,430%	0,103%	0,263%	0,273%
Q1 2008	0,437%	1,231%	0,132%	0,060%	0,219%	0,118%
Q2 2008	0,191%	0,064%	0,099%	<0,01%	0,120%	0,081%
Q3 2008	0,627%	2,536%	0,048%	0,421%	6,326%	6,739%
Q4 2008	6,639%	15,377%	0,650%	2,317%	12,280%	14,765%
Q1 2009	2,798%	10,344%	1,675%	1,920%	9,047%	5,252%
Q2 2009	2,241%	4,728%	0,470%	0,956%	4,832%	7,278%
Q3 2009	0,046%	0,819%	<0,01%	<0,01%	0,182%	2,433%
Q4 2009	0,079%	0,643%	<0,01%	<0,01%	0,016%	0,081%
Q1 2010	0,014%	0,013%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2010	0,034%	<0,01%	<0,01%	<0,01%	<0,01%	0,017%
Q3 2010	0,012%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2010	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2011	0,166%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2011	0,028%	0,136%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2011	1,452%	0,760%	0,103%	0,183%	2,316%	2,957%
Q4 2011	0,218%	0,126%	<0,01%	<0,01%	0,016%	0,033%
Q1 2012	0,091%	0,161%	<0,01%	<0,01%	0,039%	<0,01%
Q2 2012	0,014%	0,246%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2012	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2012	0,022%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2013	<0,01%	0,012%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%

Graph 2: The one year probability of default using the Merton model



Graph 3: The one year probability of default using the Hall and Miles approach



The normal state, according to the Merton method, is a probability of default of less than 0,01%. In 2008, the escalation is immense. By looking at the figures, several of the banks were in great risk of defaulting. In Q4 2008 Danske Bank had a one-year probability of defaulting by 29% meaning that if that augmentation would have lasted, the bank would on average default approximately once every three and a half years. Handelsbanken and Nordea fared of better than their competitors although they as well show alarming figures.

The results obtained from the Hall and Miles approach indicate a less extreme pattern than that of the Merton model. However, both models indicate the impact the financial crisis had. Between 2008Q3 and 2009Q2, a clear increase in both models appears with the greatest default probabilities in 2008Q4 and 2009Q1. Notable are the differences when comparing the results from the two models. According to the calculations done using the Hall and Miles approach, the financial states of Handelsbanken and Nordea appear to have been in much better shape than they were according to the Merton model. Also Danske Bank appears much more stable when looking at the Hall and Miles model, showing a default probability of less than one fourth in the last quarter of 2008, compared with that of the Merton model. Swedbank, SEB and DNB appear to have been closer to defaulting than the other banks as they show rather alarming according the Merton model but also the Hall and Miles approach.

Outside of the immediate crisis window, both models also show an increase in probability of default in 2011. During this period, the stock price of the banks decreased as well. Danske Bank's share price for example decreased in the end of 2011 to around 50% of its share price one year earlier. The share prices of the Swedish banks decreased between 18% (Swedbank) and 72% (Handelsbanken) and DNB saw a decrease of 38%. As of Q42013 all banks are, according to both models, looking at very low probabilities of default and from the results from all four quarters we can tell that 2013 was a rather stable year.

Whilst both models certainly reflect the increased probabilities of default during the crisis, for our examination it is not clear if they significantly forecast the probabilities. From the tables in appendix 3 one can see tendencies of a more unstable economic environment from 2007Q2 and onwards for the Hall and Miles approach results and from 2008Q1 and onwards for the Merton model results. Based on the fact that one can see the same tendencies in increased probability of default in 2011 (however for a shorter period of time), the small increase in probability of default before the crisis "really" hit the Nordics may not be significant enough to certainly conclude that the models forecasted the crisis. For investigation of the models forecasting abilities, it should be especially favorable to look at probability of default for Swedbank as the bank almost collapsed in October 2008. The results from the Merton model reflect an increase in the probability of default from 0,735% in 2008Q1, to 1,212% 2008Q2 and then up to 10,713% in 2008Q3. The results from the Hall and Miles approach tell a slightly different story with 0,118% in 2008Q1 and then decreasing to 0,081% in 2008Q2 before increasing to 6,739% in 2008Q3.

The measure probability of default may be somewhat deceiving. Whilst it does more clearly show the changes in the health of a company compared to the distance to default measure, one should, as we mention in the introduction, referring to Vassalou and Xing (2008), be careful not to interpret these measures literally (i.e. treat the results as rankings rather than actual probabilities of default). With this being said we would still like to highlight what we outlined above regarding the differences in the results for Handelsbanken and Nordea. These two banks showed a significant healthier pattern with the Hall and Miles approach than with the Merton model. With the Hall and Miles approach relying on market expectations to a greater extent than the Merton model, a possible part of the explanation for Nordea could be that it was partially state owned

during the crisis. This owner structure could serve as a satisfactory factor on the market however one should be very careful drawing these conclusions as DNB, which is still partially state owned, did not seem to fare as well as Nordea. When looking at Handelsbanken, the choice of staying out of the Baltic countries might be one reason that the bank fared better than the others. Swedbank, which is at the bottom of the scope, is the bank with its largest customer base in the Baltics.

6.1 GARCH(1,1)

Below are the results of the GARCH(1,1) regression based on the OMX N40 index. The Maximum Likelihood function indicates the sum in function (27) where the optimal weights are ω , α and β as seen below. The mean return is fairly close to that of the individual banks' as described in the above summary statistics. A negative skewness is shown along with a kurtosis of more than five. The series indicate strong evidence of autocorrelation which is successfully removed as demonstrated by a Ljung-Box test performed on 25 lags.

Table 5: Results from GARCH (1,1)

OMX N40	
No of obs	2346
ML function	18526.94
ω	0.0000022
β	0.9120024
α	0.0783691
γ	0.0096285
V_L	0.0002113
Skewness	-0.12886461
Kurtosis	5.0313021
Mean	0.0003267
<u>Ljung-Box</u>	
Before	2633.65
After	36.95

As all models have their withdrawals, so have the Merton model and the Hall and Miles approach. Below follow a few points of important facts and criticism that may affect our results.

- For our examination in the Merton model we assume that the bank's liability replicates a zero-coupon bond with maturity of one year. As Löffler and Posch ("Credit risk modelling using Excel and VBA" Wiley Finance (2007), p. 31) mention, this may seem as a choice based on convenience, however it can be motivated by the fact that the bank can be assumed to have a rather consistent maturity structure; hence new debt is issued in the same pace as old debt is retired. Consequently, the default probability is given for the point in time when the debt is assumed to have matured and we can measure the probability that the value of the assets at that time is lower than the debt.
- Further on, the Merton model relies on the Black and Scholes' option pricing theory. This theory relies on several assumptions which may bias the estimated asset value. The most commonly criticized assumptions of the theory are that no dividends are paid out, no commission, constant risk free rate and volatility and normally distributed returns.
- Due to the fact that we do not have access to any empirical database for converting our results obtained from the Merton model, we assume normality in the asset returns and value distribution. Thus we do not take into account that the actual distributions are heavier tailed and this may lead to an underestimation of the probability of default.
- One has to keep in mind that there are external options such as capital raising and government intervention in order to reduce the probability of default.
- Our calculations ignore the fact of fat tailed return distributions. For further studies it is appealing to apply extreme value theory as Byström (2003) does in order to more accurately imitate the return distributions. Alternatively one can examine the possibilities of substituting the normal distribution with a t-distribution as this distribution has heavier tails.

- As CAPM is used to estimate the volatility of equity in the Hall and Miles approach and to estimate the drift rate in the Merton model it is appropriate to rule out the critique that this model has met. Roll (1977) stated, in what came to be known as Roll's critique, flaws with CAPM. Most famously that the market portfolio is unobservable. The true market portfolio would need to consist of every possible asset, not limited to stocks and bonds but e.g. commodities, real estate and human capital. It is not possible to fully mimic the true market portfolio and most of the time is represented by a broad index such as the S&P 500 where we have chosen the more confined index OMX N40.
- Worth noting is that methods using stock market prices as an indicator is most likely to not reflect reality in less developed economies. However in highly developed countries such as the Nordics, stock market prices are likely to include all public information. Elsingher et al. (2006) on the other hand explain that one cannot rely fully on the financial institutions' stock market prices anywhere as there is private information that may affect an institution's risk exposure. This type of information can only be obtained from supervisory bank micro data and loan registers.

RISK LINKAGES

As a consequence of the global financial crisis, assessing systemic risk has become of greater importance. Chan-Lau (2013) informs that the crisis has led to market analysts and authorities now paying more attention to systemic risk instead of the individual risks the financial institutions would face in isolation. Under economic circumstances such as a crisis, only assessing isolated risk underestimates the risk for the financial institution in question and as well as for the whole system as the potential spillover effects are not taken into account. In this second complementary part we aim to examine the systemic risk between the Nordic banks and if any of the banks seem to have significantly stronger linkages. This kind of knowledge is important as spillover effects will deepen and broaden the secondary effects in the event of deterioration in the health of one of the banks.

7. Literature review

According to the IMF's country report "Nordic Regional Report" (2013), the Nordic countries share favorable characteristics such as high income equality, high employment and low public debt. However, the countries also face identical challenges such as for example large banking sectors, instability on housing market and high household debts. The risks of these challenges are aggravated by the countries' close economic ties and the structure of the financial markets with a few relatively large financial actors on the markets, also them with strong ties to each other.

Based on the lesson we learnt from the global financial crisis and also the structure of the Nordic banking sector, there is an importance of not only examining the Nordic banks health separately but also look at how one bank's health seems to affect the other banks.

In the same report from IMF, an experiment is performed by simulating a default of a hypothetical big Nordic bank in order to investigate the impact on the GDP in the Nordic region. The results show that the failure of the hypothetical bank could have a substantial impact on GDP in all Nordic countries and that problems in any one of the banks is likely to spread across the countries' respective financial sectors. The results from this simulation do not only indicate the important role the banks are playing but also how they are all linked to each other.

The linkages between the banks are related to systemic risk, however there are several ways of defining this risk. Kaufman and Scott (2003) summarize three definitions of systemic risk; 1: "An event having effects on the entire banking, financial or economic system, rather than on just one or a few institutions, 2: "Risk of a chain reaction of falling interconnected dominos" and 3: "Systemic risk is the similarities in third-party risk exposure". Borri et al. (2012) characterize systemic risk by three factors; " (a) it affects a substantial portion of the financial system; (b) it involves negative externalities; (c) it requires intervention of public authorities for prevention and, eventually, management of the risky environment."

With different ways of defining systemic risk come different ways of measuring this risk. As Roengpitya and Rungcharoenkitkul (2011) mention, the obvious and perhaps the most accurate way of investigating systemic risk would be to map out the linkages between financial institutions based on their balance sheets however such method would be time consuming and would produce unclear results. Borri et al. (2012) divide the literature on systemic risk into network analysis and micro-evidences. The network analysis focuses on the loss distribution of the companies examined and estimates how an eventual distress would affect the creditors while the second approach focuses on the individual company's marginal contribution to systemic risk. According to Hautsch et al. (2013) the majority of the financial network models rely on detailed data containing intra-bank assets and liability exposures that are generally not available to the public and hence difficult apply on real cases. As a consequence of this, the remaining studies cannot produce results that fully reflect a company's systemic relevance. The micro-evidence approach uses bank specific variables in order to estimate the contribution of systemic risk of each individual institution. The existing literature using this approach often relies on credit default swap (CDS) data. For instance, Segoviano and Goodhart (2009) investigates how firms contribute to systemic risk on an individual level by using their CDSs in a multivariate copula setting and Giglio (2010) measures the system default risk in a financial sector by using bond and CDS data.

For our investigation of the risk linkages between the banks we will rely on a method within the micro-evidence approach initially proposed by Adrian and Brunnermeier (2011). The authors study a large number of financial institutions impact on the system in the US during the period 1986-2010 (however, as we will review below in this section the method can be used to measure

the impact of one financial institution on another). By using the financial institutions' market-value asset returns they calculate the CoVaR and marginal CoVaR (ΔCoVaR) where the prefix Co stands for conditional, contagion or co-movement. Their definition of CoVaR is a given level of the value at risk of the system conditional on an individual financial institution experiencing distress. This distress is defined as the individual institution being at a given value at risk percentage (1% in this essay). With CoVaR the authors further calculate the ΔCoVaR . By taking the 1% CoVaR minus the "normal state" 50% CoVaR, the authors capture each institution's marginal contribution to the systemic risk. The authors calculate the unconditional CoVaR measure described above but also a conditional measure which includes macro variables in order to capture the status of the economic environment. The macro variables included are the US yield curve which is assumed to capture the short term liquidity risk, the aggregated credit spread which is assumed to control for the business cycle and lastly a volatility index to reflect investor sentiment. Finally the authors develop a forward looking ΔCoVaR , a measure to predict future marginal contribution to systemic risk. This is done by regressing the ΔCoVaR on firm specific variables such as leverage and market-to-book value. With this measure the authors show that the 2006Q4 value of this measure predicts more than 50% of the co-variances that emerged during the financial crisis.

The original VaR which was introduced and popularized by RiskMetricsTM is widely accepted as a risk measurement and aims to measure the potential losses for a portfolio, i.e. "What is the worst case scenario?". The measure has gained trust in the banking industry, especially since adopted by Basel as the primary measure to calculate market risk capital requirements. However when comparing VaR with CoVaR it becomes clear that VaR only focuses on the risk of an individual institution in isolation – In fact, Adrian and Brunnermeier (2011) show that that there is only a weak correlation between an institution's VaR and its contribution to the systemic risk.

Adrian and Brunnermeier (2011) use historical data on market-valued asset returns with quantile regression in their estimation of CoVaR, primarily due to this regression method's simplicity and efficient use of data. However the authors show that CoVaR may also be estimated with other methods such as for example GARCH models. A quantile regression is in comparison to for example Ordinary Least Square (OLS) more convenient when one is focusing on the tail ends of

a distribution. Quantile regression was introduced by Koenker and Bassett (1978) and the regression provides for each quantile a coefficient that estimates the effect in the response variable produced by a one unit change in the predictor variable. The OLS coefficient estimates the change in the mean of the response variable produced by a one unit change in the predictor variable, keeping other predictor variables fixed (Greene, *Econometric Analysis* (2011)). As an example, Koenker and Hallock (2001) examine the effect of prenatal visits on birth weight with the help of quantile regression and OLS. In this case, the authors show that OLS fail to capture useful information regarding the relationship between prenatal visits and birth weight. The quantile regression showed that the consequences of no prenatal care had a larger effect on birth weight for the new-born in the lower quantiles compared to the effect on the mean weight.

A number of recent papers have extended the CoVaR method and applied it to financial sectors. Borri et. al (2012) apply the model to over 200 European banks in order to study the contribution to systemic risk. Furthermore they use OLS to examine how different micro variables of banks affect their systemic risk contribution. They find that the variables size, leverage and concentration (i.e operating in a concentrated banking market) have a significant impact on the systemic risk contribution. A paper closely related to this essay is Adams et al. (2010) which study risk spillovers between U.S financial institutions rather than the institutions contribution to the system risk. They further refine the CoVaR by developing a “State-Dependent Sensitivity Value-at-Risk” which includes that spillovers are determined simultaneously and also focuses on the spillover effects during a crisis. They find that “size and duration of risk spillovers among financial institutions to change substantially between market phases. While risk spillovers are small during normal times, equivalent shocks lead to considerable spillover effects during crisis times” (p. 2). Their results when comparing between different classes of financial institutions also provide useful information regarding hedge funds as transmission channels and amplifiers of systemic risk. Also Roengpitya and Rungcharoenkitkul (2011) look at the spillovers between banks (and their effect on the system) by using CoVaR. They include six commercial Thai banks in their study and also conclude that the variables size and interbank deposits have a significant effect on the spillover effects from one bank to another.

While our results from using CoVaR will not show the mechanisms behind the estimated spillover, the above literature review has mentioned size, leverage, concentration and interbank deposits as significant variables. It may be of interest to mention that Bartholomew and Wharden (1995) list interbank loans, structure and diversification of the institution's portfolios and information effects among the most influent factors of the intensity and strength of interbank relations. Elsinger et al (2006) find that the correlation in banks' assets portfolios plays the biggest role in contributing to systemic risk. Hall and Miles (1990) also mention an important view – A negative externality as an information problem. A default of one bank may not theoretically affect the financial system significantly however it may lead to unstableness in the system anyway due to the undermining of confidence.

8. Method

To start with we will briefly explain the theoretical background of quantile regression and VaR that the CoVaR model relies on.

In summary there are three methods to calculate VaR. The Variance-Covariance (parametric) method assumes that the stock returns are normally distributed in order to find the worst 1% or 5% (or another value) loss on the curve. The Monte Carlo analysis produces simulated future prices and looks at worst losses of these. The historical method uses the daily returns and is similar to the parametric method but do not assume normal distribution. Instead the 1st or 5th (or another value) percentile will show the value at risk. We will follow Adrian and Brunnermeier (2010) and use the historical method (combined with quantile regression).

In terms of losses VaR can be defined as follows

$$VaR_{\alpha}(L) = \min\{l: \Pr(L > l) \leq 1 - \alpha\} \quad (30)$$

Where the probability that the future loss L is larger than minimum loss l is less or equal to $1 - \alpha$.

VaR can also generally be expressed as follows

$$\Pr(X \leq VaR_{\alpha}) = \alpha \quad (31)$$

Where x is loss, assets, CDS etc.

As previously mentioned, we will use quantile regression. In summary, a quantile regression is based on minimization of the sum of residuals with asymmetric weight on these throughout the quantiles. A conditional quantile, in (32) expressed as a distribution of Y given the distribution of X , can be defined as follows

$$Q_y(q|x) = x^Q \beta_q \quad (32)$$

for a given quantile q .

By using the above derivation we minimize equation (33) with respect to β_q in order to obtain an estimate of β_τ . This coefficient describes how much $Q_y(q|x)$ changes due to a one unit change in one of the predictor variables in vector x^Q .

$$\frac{1}{n} \sum_{i=1}^n \rho_q(y_i - x^Q \beta_q) \quad (33)$$

With this brief review, we are now ready to construct CoVaR. Recall the definition of VaR, defined as VaR_q^i as the q^{th} quantile;

$$\Pr(X^i \leq VaR_q^i) = q$$

Thus VaR_q^i is the quantile q of the log returns of firm's stock i , To this expression a conditional event is added, which defines the CoVaR of bank j conditional on bank i being at a given level of VaR.

$$\Pr(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i) = q \quad (34)$$

In words, q is the probability of the returns of bank j 's are lower than $CoVaR_q^{j|i}$ within a specified time period given that bank i experiences distress.

Further to measure $\Delta CoVaR$, how much bank i 's 1% VaR is affected when bank j is going from median state (50% VaR) into financial distress (1% VaR), the CoVaR value when bank i is in its median state is subtracted from the calculated distressed CoVaR.

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|x^i=VaR_q^i} - CoVaR_q^{j|x^i=Median^i} \quad (35)$$

In practice, to obtain each individual bank's VaR we quantile regress the respective daily returns on a constant. For this essay's interpretation of distress, 1%, the quantile value of interest is 0,01.

$$VaR_q^i = \hat{\alpha}_q^i \quad (36)$$

The log returns of bank j are then quantile regressed on the log returns of bank i ³

$$X_q^{j,i} = \alpha_q^i + \beta_q^i X_q^i + \varepsilon_q^i \quad (37)$$

The coefficients for α and β are obtained from quantile 0,01. The coefficient β estimates the change in a specific quantile of X^j produced by a one unit change in X^i . α and β are used with the VaR_q^i to estimate the $CoVaR_q^{j|i}$ in the following way

$$CoVaR_q^{j|x^i=VaR_q^i} = VaR_q^j | VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \quad (38)$$

Further to calculate the $\Delta CoVaR$ we include the 50% VaR for bank i ⁴

³ Coefficients provided in appendix 5

⁴ Note that for the calculations in this essay, the 50% VaR for all banks will be zero as conditional CoVaR is not calculated.

$$\Delta CoVaR_{q-1\%}^{ji} = \hat{\beta}_{q-1\%}^i (VaR_{q-1\%}^i - VaR_{q-50\%}^i) \quad (39)$$

For the interested reader follows here a short explanation of how the conditional CoVaR measure and spillover effects on to the system are calculated;

For a conditional CoVaR measure the log daily returns are quantile regressed on chosen macro variables that form vector M.

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\beta}_q^i M_t \quad (40)$$

CoVaR is then calculated as follows

$$X_t^{ji}(q) = \alpha_q^{ji} + \beta_{q,1}^{ji} X_t^i + \beta_{q,2}^{ji} M_t + \varepsilon_t^{ji} \quad (41)$$

$$CoVaR_t^i(q) = \hat{\alpha}_0^{ji} + \hat{\beta}_{q,1}^{ji} VaR_t^i(q) + \hat{\beta}_{q,2}^{ji} M_t \quad (42)$$

To examine the spillover effects onto the system, one simply substitutes bank j with a suitable index, in our case OMX N40.

9. Data

As in the first part of this essay, we use percentage returns of stock market data from Datastream for the period 2005Q1-2013Q4. The banks included are Nordea, SEB, Handelsbanken, SEB, Danske Bank and DNB.

Unlike Adrian and Brunnermeier (2011) we do not calculate the market-valued total assets but instead we rely on the stock prices to incorporate all public information available. Also, for

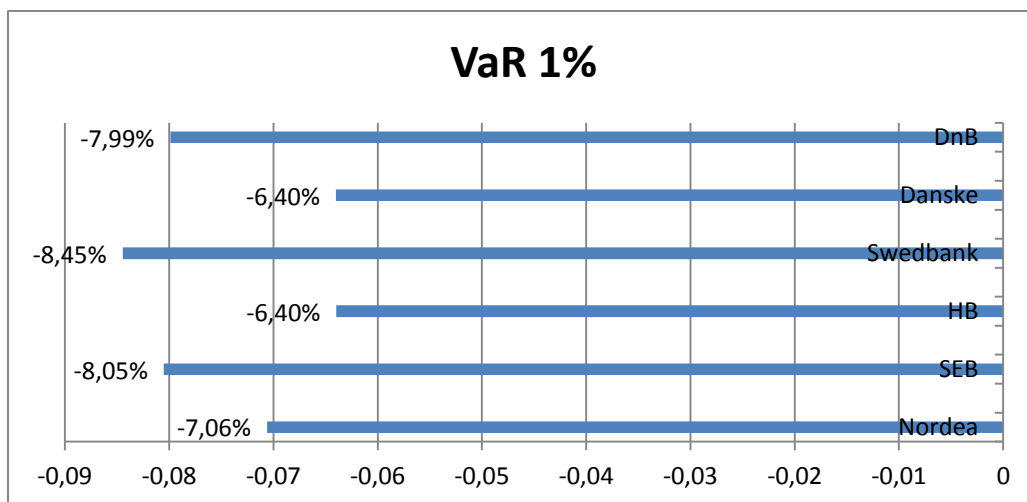
example CDS data would only reflect credit risk and we therefore confide in the stock market prices to reflect the different types of risk that exist in the system.

10. Results

Before showing our results it is important to consider that these are unconditional, constant, measures of CoVaR. Hence the regressions do not include any macro variables that would control for time-dependent variation of the tail end risk (i.e these variables would absorb some of the spillover effects). We do explain the results in percentage however our results are, just as in our first part, mainly an indicator of ranking among the banks. On the other hand, adding macro variables may give a false perception of realistic numbers however these variables may not capture all time dependent changes.

When analyzing the banks in isolation (by calculating VaR with quantile regression) we can tell from the diagram below that Swedbank is considered the most risky and Danske Bank and Handelsbanken are considered the least risky. Hence, in a worst case scenario defined as the 1% historically worst losses, Swedbank's share price would go down with 8,45% in one day while Danske Bank and Handelsbanken would risk a loss of 6,40% each.

Diagram 1: The 1% VaR unconditional on other banks



When continuing on to the 1% CoVaR, we obtain the spillover effects. As an example, the 1% CoVaR value for Nordea|SEB, 9,52% indicates that when SEB is in distress (defined as reaching its 1% VaR), the VaR of Nordea is affected by 9,52%. Handelsbanken and Danske Bank appear to be the banks least affected of other banks' distresses. From the average, one can tell that Danske Bank has the smallest spillover effect on other banks and that Nordea has the largest spillover on other banks when it is in distress. Most notably is Nordea's spillover effect on SEB and Swedbank; 14,48% and 14,02% respectively.

Table 6: 1% CoVaR with conditioning bank *i* on vertical axis and dependent bank *j* on horizontal axis

Bank <i>j</i> Bank <i>i</i>	Nordea	SEB	HB	Swedbank	Danske	DnB	Average
Nordea		-14,48%	-8,64%	-14,02%	-9,67%	-11,46%	-11,65%
SEB	-9,52%		-7,92%	-11,88%	-9,24%	-11,94%	-10,10%
HB	-10,28%	-12,42%		-12,71%	-9,17%	-12,41%	-11,40%
Swedbank	-9,54%	-12,95%	-8,88%		-9,19%	-11,54%	-10,42%
Danske	-10,20%	-11,60%	-8,88%	-13,16%		-6,07%	-9,98%
DnB	-10,52%	-11,61%	-8,92%	-12,40%	-9,27%		-10,54%

The last and most important measure, 1% ΔCoVaR^5 , quantifies how much risk bank *i* adds to bank *j*. Looking at Nordea|SEB again, the 5,07%, indicates the 1% VaR for Nordea is affected by 5,07% when SEB goes from median state (50% VaR) into financial distress (1% VaR). By looking at this marginal contribution, we are given an indication of which banks are more vulnerable in a distressed environment. Again, Nordea seems to be the bank affecting the other banks the most when going into distress. DNB and Danske Bank appear to be the banks with the lowest impact on other banks and Danske Bank is also the bank less affected by other banks in distress. Note that also for this measure SEB is particularly affected by Nordea.

⁵ See appendix 6 for period 2007-2009 and 2012-2013

Table 7: 1% ΔCoVaR with conditioning bank i on vertical axis and dependent bank j on horizontal axis

Bank j Bank i	Nordea	SEB	HB	Swedbank	Danske	DnB	Average
Nordea		-8,48%	-4,64%	-6,70%	-4,17%	-5,61%	-5,92%
SEB	-5,07%		-8,05%	-6,68%	-3,74%	-5,04%	-5,71%
HB	-5,88%	-6,82%		-6,31%	-3,47%	-5,61%	-5,62%
Swedbank	-4,84%	-7,65%	-4,28%		-3,29%	-4,84%	-4,98%
Danske	-4,40%	-5,00%	-3,68%	-6,06%		-4,82%	-4,79%
DnB	-4,82%	-5,41%	-4,22%	-5,70%	-3,97%		-4,82%

When considering the fact from previous research that the VaR is not correlated with the CoVaR, one can conclude that the same holds for this study. Swedbank has the highest VaR but one of the lower ΔCoVaR . Nordea that has one of the lower VaR comes out with the highest ΔCoVaR .

To summarize the results; overall, Nordea is the bank affecting other banks the most. Especially notable is the spillover effects from Nordea on to SEB. Danske Bank comes out as the bank with least spillover effects on the other banks. Previous literature suggests that the variable size has a significant impact on spillover effects which may partly explain the measures for Nordea. However, this is not true for Danske Bank that is also one of the larger banks of the sample. A ranking of the banks are not appropriate as the results are within a narrow span. Still, by looking an individual spillovers from one specific bank on to another, we can obtain valuable indicators.

11. Summary and conclusions

This essay has examined the credit risks and risk linkages of the six major Nordic commercial banks. It has critically reviewed the results and evaluated the chosen models. With regards to the probability of default, Nordea and Handelsbanken seem to have fared better than its peers. However, when looking at the spillover effects between the banks, these two banks appear to have the highest spillover effects on the other banks. With this kind of result it is difficult to rank the banks or appoint one bank as “safer” or “riskier” than another. An important lesson learned is

that looking at the banks in isolation is not enough to obtain a full picture of the current status of a bank.

The probabilities of default obtained from the Merton model compared to the ones obtained from the Hall and Miles approach show an overall similar trend but the ranking (and naturally also the numbers) except for the “healthier” Nordea and Handelsbanken during the financial crisis differ. None of the models seem to have forecasted the crisis significantly.

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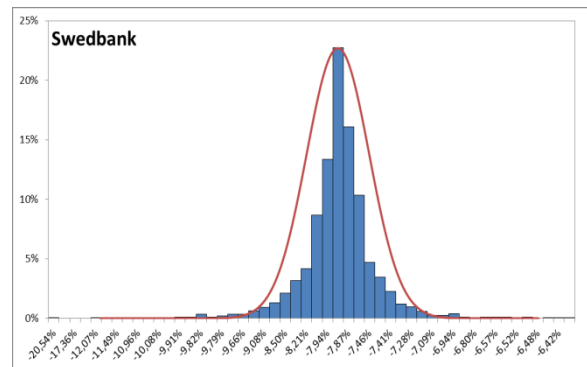
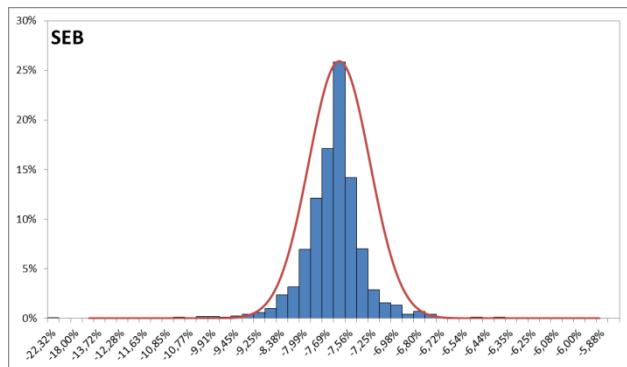
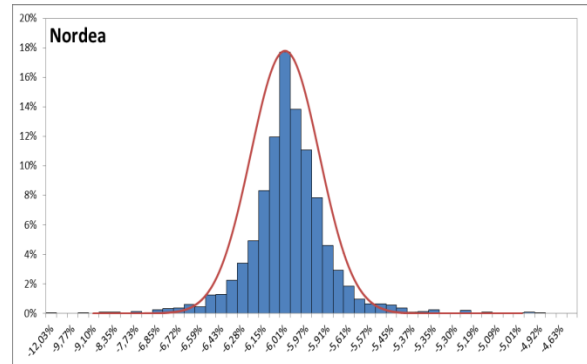
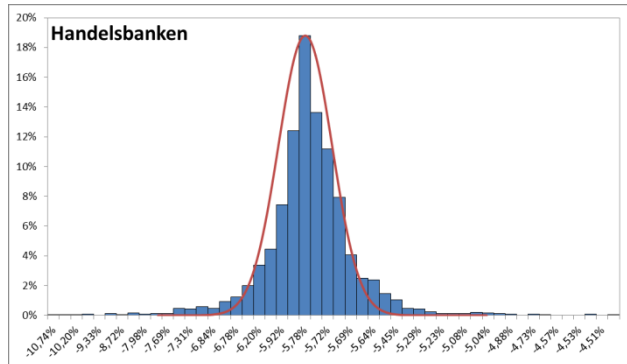
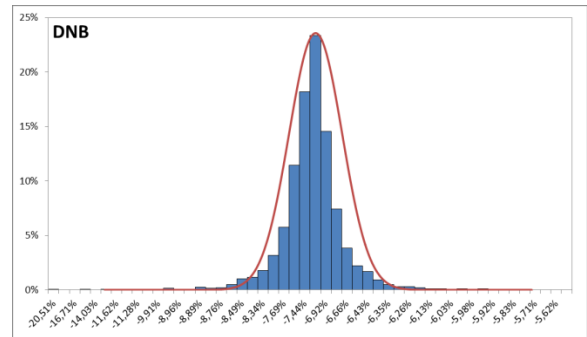
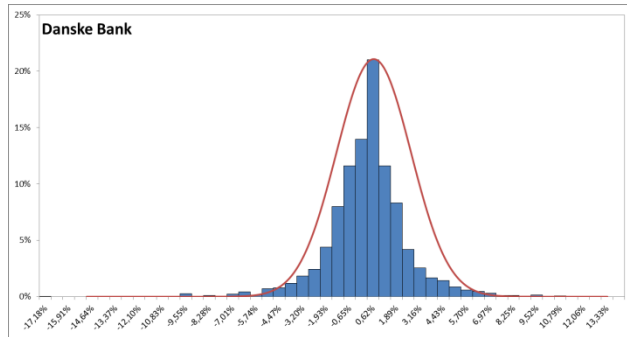
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13. Appendices

Appendix 1:

Histograms of asset returns compared to the normal distributions for the individual banks.



Appendix 2:

Yearly volatilities of the individual banks.

	Danske Bank	DNB	Handelsbanken	Nordea	SEB	Swedbank
2006	1,12%	2,21%	1,71%	1,57%	1,18%	1,72%
2007	1,06%	1,73%	1,52%	1,50%	1,61%	2,36%
2008	1,58%	2,77%	2,81%	2,44%	1,97%	2,53%
2009	1,00%	2,08%	1,92%	2,09%	1,79%	1,66%
2010	0,93%	1,87%	1,30%	1,50%	1,40%	1,59%
2011	1,14%	2,15%	1,48%	1,60%	1,67%	2,35%
2012	0,79%	1,55%	1,31%	1,00%	1,22%	1,60%
2013	0,85%	2,20%	1,52%	1,20%	1,21%	2,20%
Average	1,06%	2,07%	1,70%	1,61%	1,51%	2,00%

Appendix 3:

One year probabilities of default results using the Merton and Hall and Miles approaches.

MERTON	DANSKE BANK	DNB	SHB	NORDEA	SEB	SWEDBANK
Q2 2005	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2005	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2005	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2006	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2006	<0,01%	0,192%	0,117%	0,093%	0,130%	0,110%
Q3 2006	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2006	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2007	<0,01%	<0,01%	<0,01%	<0,01%	0,016%	0,078%
Q2 2007	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2007	0,010%	<0,01%	0,015%	0,013%	0,502%	0,410%
Q4 2007	<0,01%	<0,01%	<0,01%	<0,01%	0,242%	0,315%
Q1 2008	0,713%	0,233%	0,612%	0,315%	1,468%	0,735%
Q2 2008	0,854%	0,254%	0,421%	0,127%	1,915%	1,212%
Q3 2008	2,517%	8,150%	1,503%	2,681%	6,684%	10,713%
Q4 2008	29,144%	21,709%	12,356%	16,420%	28,163%	26,142%
Q1 2009	19,092%	10,098%	6,432%	9,877%	21,640%	20,234%
Q2 2009	1,774%	4,459%	0,701%	1,782%	4,191%	7,645%
Q3 2009	0,095%	0,720%	0,136%	0,116%	0,898%	0,885%
Q4 2009	0,436%	0,727%	<0,01%	0,052%	0,224%	0,189%
Q1 2010	<0,01%	0,030%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2010	1,667%	0,168%	0,018%	0,489%	0,782%	1,061%
Q3 2010	0,211%	0,042%	<0,01%	0,015%	0,011%	<0,01%
Q4 2010	0,014%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2011	0,306%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2011	0,096%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2011	2,374%	1,657%	0,331%	1,095%	2,655%	3,946%
Q4 2011	1,343%	1,968%	0,139%	1,453%	1,231%	0,947%
Q1 2012	0,064%	0,050%	<0,01%	<0,01%	0,022%	0,018%
Q2 2012	0,128%	0,732%	<0,01%	0,059%	0,052%	0,018%
Q3 2012	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2012	0,025%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	0,039%
Q2 2013	0,086%	0,023%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2013	0,013%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%

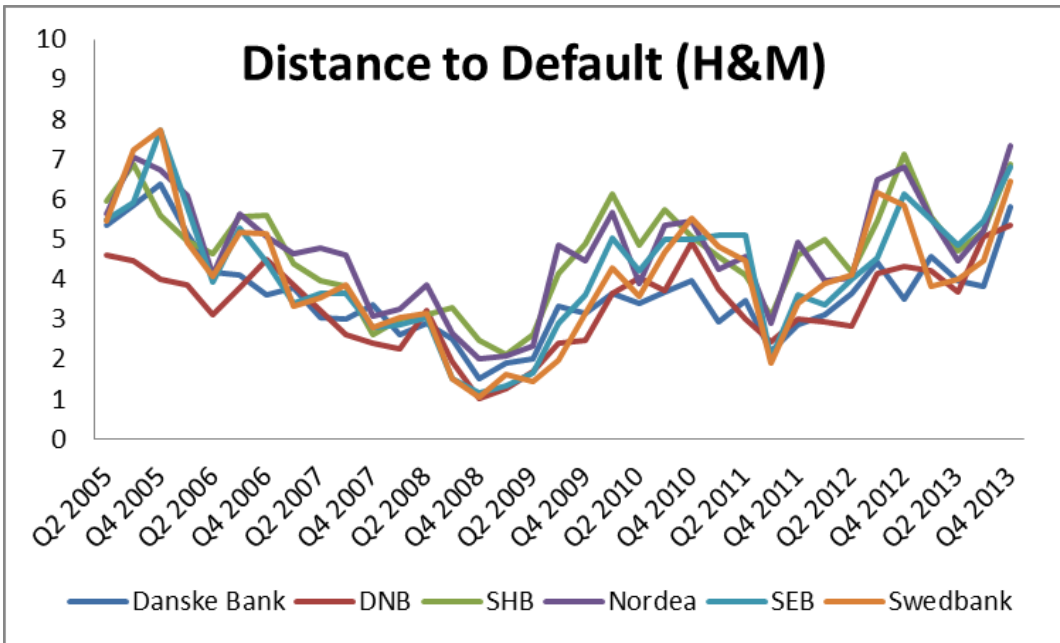
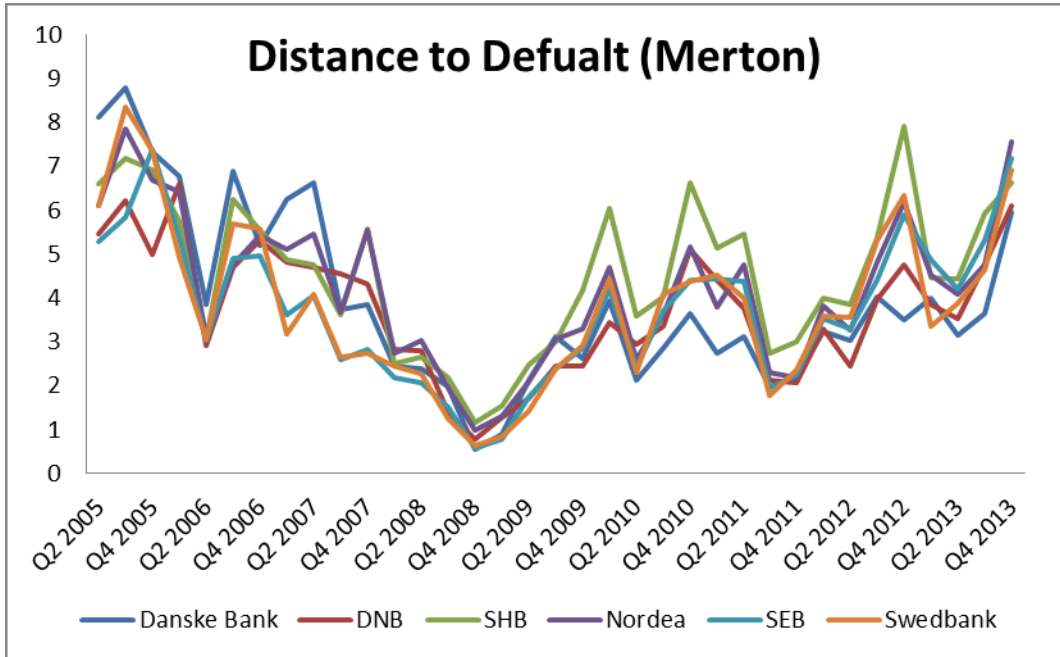
HALL & MILES	DANSKE BANK	DNB	SHB	NORDEA	SEB	SWEDBANK
Q2 2005	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2005	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2005	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2006	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2006	<0,01%	0,092%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2006	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2006	0,016%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2007	<0,01%	<0,01%	<0,01%	<0,01%	0,035%	0,046%
Q2 2007	0,120%	0,064%	<0,01%	<0,01%	0,014%	0,020%
Q3 2007	0,140%	0,434%	<0,01%	<0,01%	0,013%	<0,01%
Q4 2007	0,037%	0,828%	0,430%	0,103%	0,263%	0,273%
Q1 2008	0,437%	1,231%	0,132%	0,060%	0,219%	0,118%
Q2 2008	0,191%	0,064%	0,099%	<0,01%	0,120%	0,081%
Q3 2008	0,627%	2,536%	0,048%	0,421%	6,326%	6,739%
Q4 2008	6,639%	15,377%	0,650%	2,317%	12,280%	14,765%
Q1 2009	2,798%	10,344%	1,675%	1,920%	9,047%	5,252%
Q2 2009	2,241%	4,728%	0,470%	0,956%	4,832%	7,278%
Q3 2009	0,046%	0,819%	<0,01%	<0,01%	0,182%	2,433%
Q4 2009	0,079%	0,643%	<0,01%	<0,01%	0,016%	0,081%
Q1 2010	0,014%	0,013%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2010	0,034%	<0,01%	<0,01%	<0,01%	<0,01%	0,017%
Q3 2010	0,012%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2010	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2011	0,166%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2011	0,028%	0,136%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2011	1,452%	0,760%	0,103%	0,183%	2,316%	2,957%
Q4 2011	0,218%	0,126%	<0,01%	<0,01%	0,016%	0,033%
Q1 2012	0,091%	0,161%	<0,01%	<0,01%	0,039%	<0,01%
Q2 2012	0,014%	0,246%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2012	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2012	0,022%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q1 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q2 2013	<0,01%	0,012%	<0,01%	<0,01%	<0,01%	<0,01%
Q3 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%
Q4 2013	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%	<0,01%

Appendix 4:

One year distance to default measures and graphs using the Merton and Hall and Miles approaches.

MERTON	DANSKE BANK	DNB	SIB	NORDEA	SEB	SWEDBANK
Q2 2005	8,090	5,452	6,581	6,096	5,258	6,078
Q3 2005	8,770	6,220	7,172	7,833	5,828	8,345
Q4 2005	7,317	4,981	6,919	6,679	7,377	7,334
Q1 2006	6,758	6,571	5,725	6,418	5,364	4,915
Q2 2006	3,842	2,890	3,044	3,111	3,011	3,061
Q3 2006	6,883	4,692	6,244	4,737	4,878	5,692
Q4 2006	5,181	5,302	5,523	5,404	4,944	5,557
Q1 2007	6,222	4,804	4,852	5,090	3,599	3,165
Q2 2007	6,604	4,695	4,737	5,435	4,056	4,064
Q3 2007	3,709	4,537	3,616	3,659	2,575	2,643
Q4 2007	3,847	4,302	5,558	5,542	2,818	2,732
Q1 2008	2,451	2,829	2,505	2,731	2,179	2,440
Q2 2008	2,385	2,802	2,635	3,018	2,072	2,253
Q3 2008	1,957	1,395	2,169	1,930	1,500	1,242
Q4 2008	0,549	0,782	1,157	0,977	0,578	0,639
Q1 2009	0,875	1,276	1,519	1,289	0,784	0,833
Q2 2009	2,103	1,700	2,456	2,101	1,729	1,429
Q3 2009	3,106	2,447	2,999	3,045	2,366	2,372
Q4 2009	2,623	2,444	4,173	3,281	2,842	2,897
Q1 2010	3,933	3,435	6,019	4,678	4,199	4,423
Q2 2010	2,128	2,932	3,564	2,583	2,417	2,304
Q3 2010	2,861	3,342	4,029	3,610	3,684	4,063
Q4 2010	3,634	5,081	6,624	5,163	4,408	4,357
Q1 2011	2,742	4,394	5,133	3,779	4,424	4,500
Q2 2011	3,102	3,739	5,447	4,741	4,367	3,974
Q3 2011	1,982	2,130	2,715	2,292	1,934	1,757
Q4 2011	2,213	2,060	2,991	2,183	2,247	2,347
Q1 2012	3,221	3,291	3,994	3,804	3,513	3,569
Q2 2012	3,017	2,441	3,834	3,244	3,282	3,562
Q3 2012	4,018	3,969	5,373	4,793	4,385	5,309
Q4 2012	3,483	4,756	7,900	6,185	5,893	6,331
Q1 2013	3,981	3,828	4,442	4,512	4,863	3,357
Q2 2013	3,134	3,507	4,417	4,061	4,200	3,878
Q3 2013	3,648	4,748	5,918	4,749	5,308	4,633
Q4 2013	5,935	6,086	6,614	7,561	7,163	6,898

HALL & MILES	DANSKE BANK	DNB	SFB	NORDEA	SEB	SWEDBANK
Q2 2005	5,343	4,609	5,959	5,616	5,484	5,465
Q3 2005	5,857	4,460	6,885	7,050	5,934	7,218
Q4 2005	6,363	3,998	5,607	6,746	7,721	7,740
Q1 2006	5,138	3,865	4,946	6,111	5,826	4,930
Q2 2006	4,165	3,114	4,644	4,113	3,939	4,069
Q3 2006	4,109	3,787	5,545	5,630	5,271	5,179
Q4 2006	3,596	4,490	5,584	5,060	4,425	5,118
Q1 2007	3,778	3,852	4,403	4,635	3,390	3,316
Q2 2007	3,035	3,222	3,958	4,793	3,634	3,539
Q3 2007	2,989	2,624	3,833	4,588	3,644	3,862
Q4 2007	3,376	2,396	2,627	3,081	2,791	2,778
Q1 2008	2,622	2,247	3,007	3,238	2,849	3,041
Q2 2008	2,893	3,220	3,094	3,848	3,035	3,154
Q3 2008	2,497	1,954	3,305	2,635	1,528	1,495
Q4 2008	1,503	1,020	2,484	1,992	1,161	1,047
Q1 2009	1,911	1,262	2,126	2,071	1,338	1,621
Q2 2009	2,006	1,672	2,597	2,343	1,661	1,455
Q3 2009	3,315	2,400	4,150	4,841	2,908	1,972
Q4 2009	3,159	2,487	4,883	4,452	3,603	3,152
Q1 2010	3,637	3,653	6,138	5,680	5,026	4,299
Q2 2010	3,397	4,019	4,845	3,881	4,206	3,585
Q3 2010	3,672	3,719	5,726	5,353	4,997	4,675
Q4 2010	3,947	4,919	5,076	5,461	4,985	5,521
Q1 2011	2,936	3,767	4,566	4,241	5,086	4,804
Q2 2011	3,448	2,997	4,096	4,559	5,091	4,460
Q3 2011	2,183	2,428	3,081	2,905	1,992	1,887
Q4 2011	2,852	3,021	4,608	4,906	3,598	3,402
Q1 2012	3,117	2,947	4,985	3,967	3,363	3,878
Q2 2012	3,629	2,812	4,191	4,026	3,983	4,102
Q3 2012	4,411	4,123	5,456	6,480	4,543	6,149
Q4 2012	3,517	4,334	7,126	6,789	6,143	5,863
Q1 2013	4,573	4,203	5,546	5,511	5,506	3,830
Q2 2013	3,957	3,663	4,726	4,448	4,850	4,009
Q3 2013	3,819	5,057	5,195	5,208	5,469	4,451
Q4 2013	5,798	5,361	6,888	7,336	6,815	6,464



Appendix 5:

Coefficients for $X_q^{j,i}$ regressions

Xi		XNordea Xi	SEB	HB	Swedbank	Danske	DnB
Nordea	a		-0,060	-0,040	-0,060	-0,055	-0,065
	B(Xi)		1,2014	0,657	0,949	0,591	0,702
SEB	a	-0,042		-0,038	-0,052	-0,055	-0,069
	B(Xi)	0,063		0,512	0,830	0,464	0,626
HB	a	-0,044	-0,056		-0,064	-0,057	-0,068
	B(Xi)	0,920	1,066		0,986	0,543	0,877
Swedbank	a	-0,047	-0,053	-0,046		-0,059	-0,067
	B(Xi)	0,573	0,906	0,507		0,389	0,573
Danske	a	-0,058	-0,066	-0,052	-0,071		-0,066
	B(Xi)	0,688	0,781	0,575	0,947		0,753
DnB	a	-0,057	-0,062	-0,047	-0,067	-0,053	
	B(Xi)	0,604	0,677	0,528	0,713	0,497	

Appendix 6:*1% Δ CoVaR with conditioning bank i on vertical axis and dependent bank j on horizontal axis**2007-2009*

	Nordea	SEB	HB	Swedbank	Danske	DNB
Nordea		-10,54%	-6,46%	-6,20%	-6,04%	-8,70%
SEB	-7,27%		-6,51%	-10,31%	-7,41%	-9,33%
HB	-7,37%	-8,71%		-6,88%	-5,96%	-9,13%
Swedbank	-5,60%	-9,40%	-4,33%		-3,14%	-7,03%
Danske	-6,79%	-9,07%	-5,19%	-8,35%		-6,62%
DNB	-8,21%	-9,51%	-8,90%	-8,20%	-7,56%	

2012-2013

	Nordea	SEB	HB	Swedbank	Danske	DNB
Nordea		-2,41%	-1,45%	-2,87%	-2,38%	-2,32%
SEB	-2,54%		-2,05%	-4,72%	-1,61%	-1,64%
HB	-2,09%	-1,85%		-2,85%	-2,43%	-1,65%
Swedbank	-1,83%	-1,96%	-2,23%		-1,79%	-2,63%
Danske	-1,47%	-1,63%	-1,57%	-1,37%		-2,51%
DNB	-0,92%	-0,47%	-0,12%	-2,50%	-1,59%	