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Stock Prices and CDS-spreads as Bank Default Indicators in the European Banking Sector

Abstract

The importance of the health of the banking sector cannot be underestimated, especially not after the recent financial crisis. Credit rating agencies base their ratings on backward-looking accounting information which cannot be used to predict a bank default. Therefore, it is of high relevance to develop market-based measures of default to give a point-in-time indication of the health of the banking sector. In this study, two measures of default will be compared; one developed by Hall and Miles (1990) which is based on stock prices and second one using a CDS spread. The study will be applied on the European banking sector where the 25 banks included in the study have been selected from the European Banking Authority’s stress test. By using a GARCH (1, 1) model applied on daily stock returns significant results indicate that conditional variances add information in predicting returns. The relationship between the measures based on stocks and the CDS spreads are strongly negative for most of the banks which proves the underlying theory behind these measures.

Keywords: banking sector; default; stock; CDS; credit risk

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1. Introduction

1.1 Background

The recent financial crisis has taught us a wide range of new words, among the most common ones, and perhaps the most substantial expression is securitization. Securitization changed bank's policy from keeping the loans it originates on its balance sheet until maturity into packaging loans and other assets into newly constructed and often very complex securities, called asset-backed securities (ABS), and selling these to investors (Saunders and Allen, 2010, p. 5). By this construction banks transferred some of their liquidity, interest and credit risk from their balance sheet to investors who certainly not were aware of the underlying risk in the securities they just invested in all the times. The banks received cash by selling these securities which they used to originate new loans or assets and so this securitization cycle continued. Collateralized mortgage obligations (CMOs), collateralized loan obligations (CLOs) collateralized debt obligations (CDOs), collateralized insurance obligations (CIOs), real estate investment trust (REIT) and commercial real estate (CRE CDOs) are a few of these instruments that were introduced and heavily traded during the financial crisis which demonstrates the willingness and creativity to transfer different types of risks (Saunders and Allen, 2010, p. 6). Another credit derivative which grew rapidly during the financial crisis was the credit default swap (CDS) which allowed banks to transfer some of their risk to nonbanks, most often insurance and reinsurance companies. For insurance companies these derivatives are seen as insurance products which can be employed to insure buyers of credit protection against risk exposure to their loan customers (Saunders and Allen, 2010, p. 15).

Exactly how this relationship between the bank and the insurance company appears and the construction of the credit default swap will be explained in chapter 2, although it can already be confirmed that not all credit risk can be removed from the bank's balance sheet by this credit derivative. A credit default swap buyer may still face the counterparty risk that the seller will default on its obligation to cover credit losses incurred under the CDS contract. Trading with these types of credit derivatives may also be sensitive to free-rider problems and negative externalities such as that competitiveness among protection buyers may lead to inadequate monitoring on the seller although banks may rely on other protection buyers to make correct due diligence on the protection seller. Moral hazard may also be a problem since banks may feel secure by hedging their exposure but the protection given by the CDS contract may be fleeting if the liquidity of the CDS market vanishes or asset correlations go towards perfect positive (Saunders and Allen, 2010, p. 17).

Besides from transferring risk between different agents the CDS has another function. By using the spread, i.e. the swap fee paid by the protection buyer, a short-term forward-looking measure can be developed which measures the credit risk of the counterparty. The advantage of this measure is that it relies on market data and will result in a point-in-time rating for banks, corporate and sovereign borrowers compared to ratings giving by rating agencies such as Standard & Poor's and Moody's which rely on backward-looking accounting information (Saunders and Allen, 2010, p. 17). Earlier studies have shown that market based measures such as CDS spreads are good supplements to ratings from rating agencies (Flannery, Houston and Partnoy, 2010). This comparatively new measure will therefore be investigated compared to an already developed market-based measure involving stock prices. The business area to be studied is the European banking sector due to the fact that banks are different from other business in a plethora of perspectives; partly because they have a lot more debt than ordinary companies and partly because they are interesting to study because a bank-default may be contagious and cause insecurity in the entire sector (Clare and Priestley, 2002, p. 23). The aim of the new Basel III principles with stronger capital requirement regulations makes it even more interesting and necessary to develop further forward-looking measures to predict a possible default.

1.2 Problem discussion

Credit rating agencies evaluate companies from accounting information which is criticized for being backward-looking and for reacting slowly (Di Cesare, 2006, p. 121). At the same time recent studies have shown that changes in CDS spreads reflect new information more instant than changes in ratings by credit ratings agencies (Flannery, Houston and Partnoy, 2010, p. 2089). For these reasons it is of high relevance to develop supplementary measures of default based on market indicators such as stocks, bonds or in this case credit default swaps. For the importance of the banking sector's health in the European Union during the recent and ongoing financial crisis this measure of default will be examined for the banking sector in the European Union. The chosen banks have been selected from the European Banking Authority's stress test (EBA, 2011).

1.3 Objective

The objective of this thesis is to study whether a simplified version of the Hall and Miles (1990) approach can be employed to see if there are any differences between the market-based CDS spread and a measure developed from a GARCH (1,1) on stock data, and how these two measures correlate. A short comparison will also be made to ratings and, in particular recent changes in ratings made by the credit rating agency Standard & Poor's. Both the measures from the CDS spreads and the stocks will be calculated for the individual banks due to being able to see any possible differences in how the European banks are affected.

1.4 Limitations

Although it should have been interesting to compare the results with ratings from the rating agencies over the entire time period it will not be a part of this study due to the criticism of their use of backward-looking accounting information and instead focus on developing new market-based indicators.

1.5 Criticism

The main criticism of the method used in this paper is that this method, along with other market-based indicators based on stocks is only applicable on businesses, in this case banks, that are represented at the stock market. This means that banks which are owned completely by the government or by its customer will not be studied, although they may have a CDS.

1.6 Disposition

The remainder of this paper will be arranged as follows. Chapter 2 presents theory about credit risk; credit default swaps as well as capital regulation for banks and methods for measuring credit risk. Chapter 3 introduces the Hall and Miles approach and the simplified model. Chapter 4 presents the results while chapter 5 concludes.

2. Theory

2.1 Credit risk

Credit risk is often defined as the potential that the counterparty will not fulfill its obligations. For banks the most obvious and largest credit risk lies in their originated loans but other types of sources exist and have increased recently, for example different types of financial instruments such as acceptances, interbank transactions, trade financing, financial futures, swaps, bonds, equities, options and foreign exchange transactions. From mistakes made in the past, banks should now have an awareness of the importance of identifying, measuring, monitoring and controlling credit risk. To minimise the difficulties raised from credit risk, banks should hold capital against these risks, which is controlled by regulations. The aim of credit risk management and regulation is to maximise a bank's risk-adjusted rate of return by maintaining credit risk exposure but within acceptable parameters (Risk Management Group of the Basel Committee on Banking Supervision, 1999, p. 1).

2.2 Credit risk regulation

The Basel committee was established 1974 by the central-banks' Governors of the Group of Ten countries which included Belgium, Canada, France, Germany, Italy, Japan, The Netherlands, Sweden, Switzerland, The United Kingdom and The United States. Nowadays the Committee consists of representatives from 27 countries. The Committee lies beneath Bank for International Settlements (BIS) which is the oldest international financial organisation and whose mission is to serve central banks in their pursuit of monetary and financial stability (BIS, 2011).

The objective of the Committee's work is to formulate broad supervisory standards and recommendations which the individual authorities should implement in the way that best suit their country. However, since 1988 when the Committee released a capital measurement system, referred to as the Basel Capital Accord, the Committee's framework has contributed with detailed principles on how internationally active banks should reduce their credit risk (BIS, 2011).

2.2.1 Basel I

Basel I was established in July 1988 and was the outcome of the Basel Committee on Banking Supervision comprising of representatives of the central banks and supervisory authorities of the Group of Ten countries and Luxembourg. The two main objectives with the report on regulatory convergence were to strengthen the soundness and stability of the international banking system and to give a fair and a high degree of consistency in its application with a view to diminish an existing source of competitive inequality among international banks (BIS, 1988, p. 1). To achieve a more stable banking system, minimum levels of capital for internationally active banks were established. The aim was to focus on assessing capital in relation to credit risk although other forms of risk should also have been taken into consideration. Not only did the amount of capital matter, the quality of a bank's assets should also be regulated since it could be of doubtful value. However, the committee left the quality of a bank's assets to be monitored and regulated in the future (BIS, 1988, p. 2). The main principle in the report was the weighted risk ratio which categorised capital into different categories of assets or off-balance-sheet exposure depending on their relative riskiness where five different weights were used; 0, 10, 20, 50 and 100 % (BIS, 1988, p. 8). The Basel Committee set the target standard ratio of capital to weighted risk asset to be 8 % which international banks in the member countries should have implemented by the end of 1992 (BIS, 1988, p. 14). Hence, new methods such as complex derivatives were invented by banks to avoid the Basel regulation which enabled them to hold less capital than proposed.

2.2.2 Basel II

The revised framework's objective was to further strengthen the soundness and stability of the international banking system. The committee itself thought that the major benefit with the revised version was its stronger risk management practices by the banking sector. The framework was based on three pillars; minimum capital requirements, supervisory review and market discipline. Regarding the capital requirements, the revised version maintained 8 % as the minimum requirement of capital to be hold in risk-weighted assets (BIS, 2005, p. 14).

2.2.3 Basel III

During the recent financial crisis the Basel committee has been working on the third version of the Basel-principles. The objective with these new reforms is to strengthen global capital and liquidity principles to achieve a more resilient banking sector. The framework is extended with the purpose that the principles should improve the banking sector's ability to absorb shocks arising from financial and economic stress. The committee states in the report that the reasons why the financial crisis became so severe were that banks had built up excessive on-and-off balance sheet leverage at the same time as the level and quality of the capital base were eroded step by step (BIS, 2010, p. 1) To be able to deal with the market failures which appeared during and after the crisis, the committee's reforms are extensive on both the micro-level as well as the macro-level with reforms to strengthen the bank-level individually as well as addressing system-wide risks and the procyclical amplification. The framework builds on the three pillars from the Basel II and is extended to achieve both higher levels of quantity as well as quality of the capital base (BIS, 2010, p. 2). As in the previous Basel-principles capital is divided into different categories, some are the same as from Basel I and II and some are revised. The minimum requirement of capital will still be 8 % but additionally banks should hold more capital in form of a capital conservation buffer and a countercyclical capital buffer which will result in a total capital requirement between 10.5 and 13 % (BIS, 2010, p. 12).

2.3 Hedging credit risk

Banks have developed various techniques such as bond insurance, netting, marketing-to-market, collateralisation, termination and reassignment to reduce their exposure to credit risk. These techniques reduce credit risk by mutual agreements between the investor and the seller but they do not separate credit risk from underlying positions. This has opened up for the credit derivative market. With these products, financial institutions and investors can control their credit risk exposure by separating credit risk from market risk without dealing with relationship management concerns (Crouchy, Galai and Mark, 2001, p. 441). Credit derivatives are more than instruments of transferring risk, they also price credit risk in a more market efficient way and determine credit spreads. This makes credit risk not only the risk for default, but even the risk for changes in credit premiums which affects the relative market value of the underlying instruments such as bonds, loans and other derivatives (Crouchy, Galai and Mark, 2001, p. 442).

Commercial banks and investment banks initiated the market for credit derivatives in the early 1990s. These instruments are over-the-counter financial contracts that have payoffs sensible to changes in the credit quality of a certain issuer. The reason why the market for credit derivatives has grown so rapidly is because of the derivatives ability to create a demand both from banks, investors and other financial institutions. Banks employ them to shift aside part of their credit risk while investors and financial institutions utilise them to increase their investment yield by exposing themselves to even higher credit risk Crouchy, Galai and Mark, 2001, p. 449). Commercial banks find credit derivatives useful since they nowadays only consider it profitable to originate new loans instead of holding them until maturity due to economies of scale. When banks manage their loan portfolio they try to diversify away idiosyncratic credit risk and only keep known risk. This can be done with credit derivatives which are considered an efficient way of transferring the synthetic part of the credit risk of a loan portfolio. The advantage of this is that the bank does not have to sell or remove loans from their balance sheet which can harm the relationships between the bank and its customers (Crouchy, Galai and Mark, 2001, p. 450).

During time periods of low interest rates investors are trying to find other ways to enhance their yields, perhaps by investing across nontraditional markets. This might lead to that investors have to give up on credit quality and accept longer maturities. However, capital regulations, such as the Basel-principles, restrict banks from investing in non-investment-grade instruments. Credit derivatives on the other hand provide investors with access to high-yield markets by combining traditional investment products with derivatives (Crouchy, Galai and Mark, 2001, p. 451). The credit default swap, one of the most employed and well-known credit derivatives due to playing a significant role in the recent financial crisis, will be described below.

2.4 Credit default swaps and default probability

A credit default swap is designed to allow the contract-buyer, for example banks and other financial institutions to transfer risk from a loan portfolio to the contract seller, often an insurance company or a hedge fund. The great advantage for the contract-buyer is that the bank does not have to sell or in any other way remove loans from their balance sheet, which can harm the relationship with the bank's customers. For the protection seller, the credit derivative serves as an insurance product since it insures the contract buyer from credit risk exposure to their loan customers. The risk is thus not totally off the balance sheet since there is a risk that the protection seller itself will default (Saunders and Allen, 2010, p. 16).

The protection seller agrees to compensate the protection buyer if a reference entity experiences a default or a similar credit event. As for any insurance product, the insurance company does not take on credit risk without any compensation, the contract buyer has to pay a premium to the contract seller which is usually quoted yearly but paid quarterly. The size of this premium is called the swap spread and is the internal rate of return that is equal to the present value of the periodic premium payments to the expected payments in the event of a credit event occurring (Saunders and Allen, 2010, p. 244). The terms of agreement are often documented through a standard form created by the International Swaps and Derivatives Association (ISDA) (Flannery, Houston and Partnoy, 2010, p. 2087).

There are two major types of a credit default swaps; the total return swap and the pure credit default swap. The total return swap contains, apart from credit risk, of market risk since it is sensitive to changes in the interest rate, like for example the LIBOR rate. The pure credit default swap was developed to reduce this risk by avoiding the element of market risk and is now strongly dominating the credit default swap market.

There are four characterising terms that describe a credit default swap:

- The identity of the reference loan is characterised by the notional value, time to maturity and the credit spread on a loan issued by the reference obligator, the contract buyer.
- The definition of a credit event is usually one of the following; bankruptcy, prepayment, default, failure to pay, repudiation/moratorium or reconstructing.
- The compensation that the protection seller will pay the protection buyer if a credit event triggers.
- Specification of either physical settlement or cash settlement (Saunders and Allen, 2010, p. 248. p).

The definition of a credit event is of high relevance to be stated in the contract and is often standardised. The most common form of a credit event is the failure to pay by the reference entity (Flannery, Houston and Partnoy, 2010, p. 2087).

A credit default swap contract can best be described by a picture such as the one seen below.

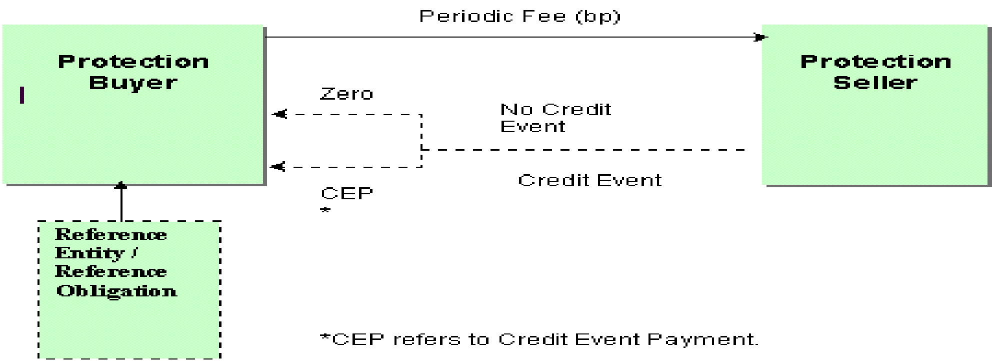


Diagram 1. Credit default swap (RBI, 2011)

The CDS market is measured in terms of the notional amount of outstanding transactions which refers to the par amount of credit protection bought or sold. From this information the premium payment can be derived for each payment period and the recovery amounts of a credit event. The CDS industry have agreed on reducing the number of trades outstanding where the objective is to keep the same risk profile but decrease the number of CDS contracts held by participants. This compression in the CDS market has resulted in a value of $25.5 trillion in gross notional CDS and $2.3 trillion in net notional value as of December 31, 2010 (ISDA, 2011).

2.4.1 Credit default swap spread

The price of a CDS contract is the same as the size of the premium paid by the protection buyer i.e. the CDS spread. The CDS spread changes over time depending on the demand and supply for a certain contract, similar to insurance premiums which reflect the market participants' estimation of the risk of a credit event associated with the underlying obligation (Flannery, Houston and Partnoy, 2010, p. 2088). Though CDSs are heavily traded they reflect market information well of the credit risk of the underlying financial obligations. Flannery, Houston and Partnoy (2010) have shown that changes in the CDS spreads reflect market information more promptly relative to changes in credit ratings by rating agencies. They also conclude that both CDS spreads and equity prices identify changes in risk when they occur but neither of them could predict the problems of the major banks before 2007, when both the CDS spreads and equity markets were relative constant and showed no ostentatiously movements (Flannery, Houston and Partnoy, 2010, p. 2111).

The single named CDS is especially interesting as a measure of default since it reflects pure issuer default risk, not issuer specific risk. Together with the liquid market of CDS contracts this should make CDS spreads a perfect benchmark for measuring and pricing credit risk (Norden and Weber, 2009, p. 530).

2.5 Stocks and default probability

During the years a plethora of studies have tried to develop different measures to predict default, especially on the banking sector. Santomero and Vinso (1997) developed two methods to estimate the default exposure of the commercial banking industry where both obtained movements of the total capital account as stochastic time-series. When the distribution of these movements buffered, the methods could be employed to analyse the expected future and the implication for default. In another study, by Shick and Sherman (1980) bank stock prices were investigated to see whether they could function as an early warning system. They found out that changes in the regulatory rating of a bank were reflected in the bank's stock price. However, the focus for this thesis is the measure of default using stock prices developed by Hall and Miles (1990) which will be described at the next page.

2.5.1 Hall and Miles (1990)

Hall and Miles' objective was to contribute with some new techniques to measure the risk of institutions' portfolios with the aim of reducing default probabilities (Hall and Miles, 1990, p. 107). Their suggestion was to employ stock prices to measure time-dependent volatilities with the underlying assumption of market efficiency. The idea behind their approach was that if the event where the market assesses the expected value of a financial intermediary could be modeled, then the variability in the actual market valuations around their expected values could be employed to estimate the market's perceptions of the volatility of the institution's underlying portfolio (Hall and Miles, 1990, p. 111). Their estimation technique rested upon the idea that if the stochastic or unexpected element in the return on an asset rises in one period this increases the perceived risky or random element in the future. To bring people's perception of underlying volatility back down, one period of less volatile returns will be required. The ARCH model presented in their study provides a way of testing hypotheses about how exactly changes in balance sheet structure influence the perceived volatility of the value of financial intermediaries' capital (Hall and Miles, 1990, p. 111). The results for the four banks that were included in the study; Barclays, Midland, National Westminster and Lloyds over the period June 1975 until September 1987 suggested that the hypothesis that it is only the variances of market returns that matters could not be rejected. Hence, the results indicated that conditional variances add information in predicting returns on individual assets and that conditional covariances with the market return were not sufficient to measure risk (Hall and Miles, 1990, p. 117).

2.5.2 Clare and Priestley (2002)

Clare and Priestley adapted the Hall and Miles approach and extended it to calculate the default probability of the Norwegian banking sector using stock prices. They provided a conditional measure of the probability of bank default to analyse changes in perceived risk level during the Norwegian banking crisis which peaked in December 1991 (Clare and Priestley, 2002, p. 21). By estimating a conditional form of the CAPM they obtained estimates of ε_{it} using a multivariate Asymmetric Generalised Autoregressive Conditional Hetereoscedaticity in Mean model (AGARCH-M) which allows for price asymmetries for the conditional variance of the individual stock (Clare and Priestley, 2002, p. 28). After they had obtained the measure of probability, $1/\sigma_{\varepsilon_{it}}$, they were able to measure the conditional probability of the Norwegian bank stocks. Their sample contained nine Norwegian commercial banks within the period from 1980 to 1995. They concluded that all of the failed banks had negative mean returns, which was also true for the entire banking sector (Clare and Priestley, 2002, p. 31). They also obtained presence of an asymmetric effect for the banking sector but not for the market index. Due to this they estimated an AGARCH-M model for the banking sector and a standard GARCH-M model for the market index. Both estimations fitted the data well and Clare and Priestley could therefore conclude that a leverage effect was important for banks (Clare and Priestley, 2002, p. 32). They also concluded that the measures for probability of default increased from the mid 1980s when major reforms and deregulation occurred in Norway until the crisis peaked in 1991. After the peak, the probability of default began to fall and returned to pre-crisis levels for individual banks as well as for the entire sector (Clare and Priestley, 2002, p. 39).

2.5.3 Byström (2004)

Byström employed the Hall and Miles approach to an aggregated banking sector in 34 different countries for the time period 1994 to 2002 as it contained the Asian crisis. He extended the approach by transforming estimated default measures into actual probabilities of default (Byström, 2004, p. 5). In his study he also investigated whether different structural features such as the regulatory environment, ownership, the quality of government, the financial structure and the efficiency of the banking sector were related to the market's perception of the stability of the banking system. The results for the probabilities of default for the developed world and the emerging world, respectively, showed that the market did not believe in a world-wide collapse. At the top of the Asian crisis the probabilities of default peaked both for the developed world as for the emerging world. The probabilities of a collective bank default was not only higher for the emerging world but was also kept at an elevated level for a longer period after the crisis. Hence, for the emerging world the market's assessment of the risk of a systemic bank default had decreased while it increased for the developed world. This was explained by the burst of the IT/Telecom boom which mostly affected banks in the developed world (Byström, 2004, p. 13). For the individual banks the results were mixed, although one clear pattern was noticed; the significant rise in default risk at the start of the Asian crisis and the common pattern of high levels during the crisis, included a clear peak and finally a decrease at the end of the crisis. The results from correlations between the structural factors and the probabilities showed that both the amount of regulative restrictions and the degree of state ownership were positively correlated with bank fragility while good government was negatively correlated with bank fragility. However, during the crisis, only two of the structural parameters; good government and the existence of an explicit deposit insurance scheme were significantly negatively correlated with the market's view of how probable a systematic crisis was to occur. In his study OLS regressions were run of the default probabilities on the structural parameters, the regressions were made both one at a time and jointly in a multiple regression approach (Byström, 2004, p. 15). From the results for the univariate regressions most of the structural factors had significant regression parameters before the crisis. More regulated and more state-owned banks were related to higher probabilities of default while a good government was negatively related to the banking sector's fragility. An interesting result was that more market-based economies were expected by the market to have less fragile banking sectors (Byström, 2004, p. 16).

2.5.4 Byström (2006)

Byström have also employed the Hall and Miles approach to study the Swedish banking sector by once again transforming the measure of the distance to default into a failure default probability. He also extended the approach by employing the extreme value theory to receive the default probabilities instead of assuming a normal loss distribution as Hall and Miles (Byström, 2006, p. 3). To obtain an estimate of the distance to default measure, Byström chose a bivariate GARCH-M framework. In order to avoid obtaining too many parameters Byström limited his study to a GARCH (1, 1) and chose the constant correlation representation for the covariance matrix together with the assumption of the market price of risk being constant. From this he received 10 parameters to estimate using the method of maximum likelihood (Byström, 2006, p. 11). The results for the probability of default showed that for the financial index and the manufacturing sector, where the latter was included to represent the non-financial sector, were trending upward over the sample length, although there was an exception during the period for the banking crisis when the stock market assigned very different default probabilities for the two indices. During the worst period of the banking crisis when very high default probabilities occurred, the extreme value theory did not seem to change the normal results (Byström, 2006, p. 16).

2.6 The co-movement of the CDS and stocks

Norden and Weber (2004) employed an event study to examine whether and how stocks and CDSs react to rating agencies' announcements. They tested whether rating announcements conveyed new market information and if there were any differences in efficiency between the stock market and the CDS market in the sense of credit rating changes. They tested the hypothesis that CDS spreads respond earlier to rating events than stock prices and argued that it should have been the case since there might have been a smaller fraction of noise traders in the CDS market, due to that trading in the CDS market is more strongly linked to credit risk than trading in the stock market. Another argument was that internal rating assessments change more often than externals and banks usually rely on both internal and external information when investigating large borrowers. However, equity volatility is an important input factor for pricing CDS and therefore there might be a close link between the movements of the CDS market and the stock market (Norden and Weber, 2004, p. 6). They concluded that the CDS market reacted earlier than the stock market with respect to reviews, a signal before an actual rating announcement, for two out of three rating agencies (Norden and Weber, 2004, p. 25). In another study they investigated the co-movements of credit default swaps, bonds and stocks. The aim was to investigate how the relationship between credit default swaps, bonds and stocks appeared and if they could find any lead-lag effects (Norden and Weber, 2009, p. 530). They found out that stock returns led both the credit default swaps and the bond market. The result also indicated that credit default swap market was more sensitive to the stock market than the bond market. In their study, they set up different hypothesis to answer; first that positive stock returns were associated with negative CDS spread changes and bond spread changes and second that stocks and the CDS market led the bond market. The second hypothesis was based on earlier research which suggested that information was reflected earlier in the stock market than in the bond market and those institutional features of the stock market allowed for a continuous flow of transactions that could not be established in the bond market. Norden and Weber suggested that this should have been true for the CDS market as well (Norden and Weber, 2009, p. 532). From their results they could conclude that stock returns were significantly negatively related with CDS and bond spread changes. They also concluded that stock returns were the least predictable while bond spread changes were the most predicable. Finally they concluded that this negative relationship between stocks, CDSs and bonds was clearer between the stock market and the CDS market than between the stock market and the bond market (Norden and Weber, 2009, p. 554).

2.7 GARCH

Engle (1982) presented autoregressive conditional heteroscedastic (ARCH) processes in his study as a reply to traditional econometric models that assumed a constant one-period forecast variance. The ARCH processes were mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances (Engle, 1982, p. 987). The ARCH processes seemed reasonable since it is unlikely that the variance of the residuals is constant over time in the context of financial time-series (Brooks, 2008, p 386). The ARCH processes turned out to be useful when modeling volatility clustering; a tendency of large changes in asset prices to follow large changes and small changes to follow small changes, i.e. the current level of volatility tends to be positively correlated with its level in the previous period (Brooks, 2008, p 387). In order to separate the conditional and unconditional variances of a random variable the distinction between the conditional and unconditional mean can be used. The conditional variance of u_t, the random variable will be denoted σ_t^2 and is equal to:

$$\sigma_t^2 = var(u_t|u_{t-1}, u_{t-2}, \dots) = E\left[\left(u_t - E(u_t)\right)^2 |u_{t-1}, u_{t-2}, \dots\right]$$

By assuming that $E(u_t) = 0$ we have:

$$\sigma_t^2 = var(u_t|u_{t-1}, u_{t-2}, \dots) = E[u_t^2|u_{t-1}, u_{t-2}, \dots]$$

The equation above states that the conditional variance of a zero mean normally distributed stochastic variable u_t is equal to the conditional expected value of the squared u_t. The ARCH model models the autocorrelation in the volatility by allowing the conditional variance of the residual term, σ_t^2 to depend on the previous value of the squared error which makes the ARCH (1) to appear:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

For the general case where the error variance depends on *q* lags of squared errors, the ARCH (*q*) model looks like:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \alpha_q u_{t-q}^2$$

Although ARCH models provided a framework for the analysis of time-series models of volatility they contained some difficulties resulting in a decrease in the employment of them. Among the challenges for the ARCH models were the problems of deciding how many lags of the squared error to be employed and the fact that the number of lags of the squared residuals that were required might have been very large which could result in a large conditional variance model that was not parsimonious (Brooks, 2008, p. 391).

The Generalised ARCH process was introduced as a solution to these problems by allowing for both longer memory and a more flexible lag structure (Bollerslev, 1986, p. 308). A flexible lag structure means that the GARCH model allows the conditional variance to be dependent upon its own previous lags which result in the simplest GARCH model to look like:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where the constant α_1, the ARCH-coefficient α_1 and the GARCH-coefficient β should all take a value of zero or higher and the sum of the ARCH-coefficient and GARCH-coefficient cannot exceed 1. A high value of β indicates that volatility is persistent and takes a long time to change while a high value of α means that volatility reacts quickly to market movements (Dowd, 2005, p. 132). σ_t^2 represents the conditional variance since the estimate for the variance is calculated one-period ahead based on any past information. By employing the GARCH model it is possible to interpret the current fitted variance as a weighted function of a long-term average value which is dependent on the intercept α_0, information about volatility from the period before, $\alpha_1 u_{t-1}^2$, and the fitted variance from the model during the previous period, $\beta\sigma_{t-1}^2$ (Brooks, 2008, p. 392). Although a GARCH (1, 1) model can be extended into a GARCH (*p, q*) formulation where the conditional variance depends on *q* lags of the squared error and *p* lags of the conditional variance a GARCH (1, 1) is in general sufficient to capture the volatility clustering in the data and is well accepted in the academic finance literature (Brooks, 2008, p. 394).

2.8 Integrated GARCH

Engle and Bollerslev (1986) introduced the Integrated GARCH (IGARCH) model to handle with the concern of presence of unit root in high frequency financial data. In the IGARCH model shocks to the conditional variance are constant and therefore remain important for forecasts of all horizons (Engle and Bollerslev, 1986). In other words, the Integrated GARCH model is applicable when the return series is not stationary, i.e. it contains a unit root and therefore the long-term variance does not exist (Dowd, 2005, p. 135). The ARCH-parameter α_1 plus the GARCH-parameter β becomes 1 and the GARCH (1,1) model therefore looks like:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + (1-\beta)x_{t-1}^2$$

The IGARCH model implies that the return series is not covariance stationary and that multiperiod forecasts of volatility will trend upwards. In recent studies on quasi-maximum likelihood estimation in GARCH models it has been paramount to allow the ARCH-coefficient and the GARCH-coefficient to be very close to 1 or in some case, even exceeding one (Jensen and Lange, 2007, p. 2).

2.9 Estimation of GARCH

To estimate a GARCH model the maximum likelihood technique is employed. The maximum likelihood forms a log-likelihood function, a set of parameter values are chosen that are most likely to have generated the observed data (Brooks, 2008, p. 393). First a likelihood function, *LF*, a multiplicative function of the actual data is formed which will be difficult to maximise with respect to the parameters. By taking the logarithm, the likelihood function is turned into an additive function of the sample data. To maximise the log-likelihood function, methods for homoscedastic models can be employed by modifying the variance from being assumed constant to being time-varying. Methods to maximising *LLF*, search over the parameter-space until the values of the parameters that maximise the log-likelihood function are found (Brooks, 2008, p. 396). If, for example, the *LLF* only has one maximum, any method should be able to find it although it can take more or less time. Hence, for nonlinear models such as the GARCH model, the *LLF* can have a plethora of local maxima which leads to different algorithms could find different local maxima of the *LLF*.

3. Methodology

3.1 Background to the model

Earlier studies have developed different measures to calculate expected defaults for banks; however most methods are based on accounting information and not on market-based data. The negative side of using accounting information is that the developed measures are backward-looking and is often released with a time lag. The calculated measure will therefore not give an accurate indication of the probability of default in the future since only backward-looking information is used (Clare and Priestley, 2002, p. 26). Due to this disadvantage it is of relevance to further develop measures based on market-data which can be forward-looking and indicate a signal of default before the credit event.

3.2 The Hall and Miles approach

The underlying assumptions and method employed by Hall and Miles will be described in the paragraphs below.

Hall and Miles begin by stating some assumptions underlying their method. For a typical bank they assume both the assets and liabilities to be priced efficiently by the market (Hall and Miles, 1990, p. 110). This assumption states the stock price, S_t to be calculated as:

$$S_t = \frac{1}{N}\sum_{i=1}^{I} P_{it}X_{it} \tag{1}$$

Where N is the number of outstanding stocks, P_{it} is the price of the bank's asset or liability *i* at time *t*, and X_{it} is the amount of the asset/liabilities at time *t*. Given this assumption the expected value of the stock together with the variability of the value around this expectation, an indication of probability of the bank actually defaulting can be received. A large number of standard deviations of stock capital at time *t* indicate a small probability of default and vice versa.

According to the capital asset pricing model, the return on a share of a bank depends on the risk free rate and the expected or perceived risk of the asset:

$$E(R_t) = \frac{E(S_t - S_{t-1})}{S_{t-1}} = RF_t + RP_t \tag{2}$$

Where $E(R_t)$ expresses the expected return of a stock at time *t*, RF_t the risk free return at time *t* and RP_t represents the time varying risk premium.

Expectations about future stock prices are formed one period before, i.e. in period *t-1*. The risk premium expresses what an investor has to be compensated for multiplied by the market price of this risk, λ_t. Due to the CAPM only non-diversifiable risk is costly risk and the model also has the implication that this measure of risk is part of the conditional variability in the bank's stock price. The share price is correlated with the return on an efficiently diversified market portfolio and therefore can the expected non-diversifiable risk be denoted as:

$$E(R_t) = RF_t + \lambda_t E(ND_t) \quad (3)$$

Where $E(ND_t)$ is the expression for expected non-diversifiable risk. If this holds, the actual return on the bank's shares between the period *t-1* and *t* will be equal to the expected return from the equation above plus a random residual which is assumed to be zero on average (Hall and Miles, 1990, p. 111). This gives us:

$$R_t = RF_t + \lambda_t E(ND_t) + \varepsilon_t \quad (4)$$

The expected value of capital at time *t*, $E(S_t N)$ can be derived by rearranging above equations into:

$$E(S_t N) = S_{t-1} N\{1 + RF_t + \lambda_t E(ND_t)\} \quad (5)$$

The volatility of $S_t N$ about its expected value depends on the stochastic error term, ε_t, rearranging equation (5) we have:

$$S_t N = S_{t-1} N\{1 + RF_t + \lambda_t E(ND_t) + \varepsilon_t\} \quad (6)$$

By dividing the actual value of bank capital at time *t* into a deterministic part and a stochastic part we have:

$$S_t N = E(S_t N) + S_{t-1} N \varepsilon_t \quad (7)$$

Thus we have the conditional variances, as measured at *t-1*, of the value of bank capital at time *t*:

$$(S_{t-1} N)^2 \sigma_{\varepsilon t}^2 \quad (8)$$

Where $\sigma_{\varepsilon t}^2$ is the variance of ε_t at time *t*. This variability measure is of high relevance for a regulator since it is the variability in the market value of the capital funds around the market's expected value.

By dividing the value of the bank, $S_{t-1}N$, by its standard deviation $S_{t-1}N\sigma_{\varepsilon}t$ they obtain a measure of how probable a default by time *t* is, on the condition of market efficiency (Hall and Miles, 1990, p. 112).

$$\frac{S_{t-1}N}{S_{t-1}N\sigma_{\varepsilon t}} = \frac{1}{\sigma_{\varepsilon t}}$$

As seen, this express the number of standard deviations the value of the bank represents at time *t-1*, by assuming that the residual follows the normal distribution this expression can be converted into a measure for probability of default. This measure will be employed in a more simplified version, described below, than the one used by Hall and Miles (1990), Clare and Priestley (2002) or Byström (2004, 2006).

3.3 A simplified version

This study will concentrate on the individual banks and to develop a forward-looking measure of the probability of default, 1/σ, where σ represents the conditional variances from using a GARCH (1, 1) model for each of the 25 banks. By using this simplified version of the Hall and Miles approach and comparing it to CDS spreads level for each bank an easier measure could be developed where the correlation between this simplified measure and the CDS spreads are expected to move towards perfect negative.

3.4 Selection

The banks included in the study have been chosen from the European Banking Authorities stress test which includes 90 of the largest banks in Europe. In this study it has only been possible to include 25 of these due to restrictions such as the banks must be represented at the stock market, they must have a credit default swap and the data length could not be too short.

3.5 Data

For the 25 banks that were left the stock prices and the CDS spreads for senior swaps were collected for five-year quotes which are the most common ones. Senior swaps were chosen instead of junior ones of reasons that senior swaps were more common and resulted in a larger amount of banks. All data have been downloaded from Datastream. The period is however quite short and reaches from

2004-06-08 to 2010-09-30 due to include as many banks as possible but still remain not too short time-series and some difficulties when downloading the data.

4. Results

4.1 Results on daily return series

In the table below the 25 selected banks are presented together with the results from calculations on mean, standard deviation, kurtosis and skewness on daily stock returns for the entire period. The mean returns are quite similar for all banks; very close to zero. Nine of the 25 banks exhibit negative mean return, however, they are all quite near zero and it is difficult to see any clear pattern, except for the fact that three of them are established in Italy and two in Spain. The standard deviations lie in the interval between 0.017764 and 0.050249. The two most volatile banks are established in the Western Europe; Allied Irish Banks and Royal Bank of Scotland Group. The results on kurtosis are much more mixed with an interval between 5.244192 and 85.578023 which strongly indicates that the daily return data is not normally distributed, which is, however, quite usual for frequency financial data on returns. The interval for the results on skewness reaches from -2.344470 to 4.365352 but for most of the banks the skewness is somewhere between 0 and 1. The two banks with the lowest respectively highest value of skewness are both British banks.

Table 1. Results on daily return series

		Mean	Std	Kurtosis	Skewness
Austria	Erste Bank Group	0,000499	0,031728	6,676505	0,239284
Belgium	KBC Bank	0,000498	0,038314	27,319666	1,242079
Denmark	Danske Bank	0,000199	0,022116	7,143075	0,216737
France	BNP Paribas	0,000364	0,026030	13,020558	0,982556
	Credit Agricole	0,000082	0,027841	9,858406	0,840789
	Societe Generale	0,000137	0,027652	9,203858	0,482600
Germany	Deutsche Bank AG	0,000102	0,026681	14,404462	0,943729
	Commerzbank AG	-0,000021	0,030790	10,953600	0,248782
Ireland	Allied Irish Banks Plc	-0,000610	0,050249	19,910388	-0,179080
Italy	Unicredit S.p.A	0,000008	0,026693	10,584077	0,667173
	Banco Popolare S.C	-0,000342	0,025068	8,485024	0,109614
	Banca M. D. P. di Siena S.p.A	-0,000268	0,018479	5,244192	0,161041
	UBI Banca	-0,000204	0,018362	7,051354	0,197148
Portugal	Banco Comercial Portugues, SA	-0,000410	0,020049	6,621786	0,504810
Spain	Banco Santander S.A	0,000320	0,021986	14,081132	0,920663
	Banco Popular Espanol, S.A	-0,000190	0,020936	11,739428	1,117658
	Banco Pastor, S.A	-0,000104	0,017764	5,317094	0,536461
Sweden	Nordea Bank AB	0,000586	0,022967	7,391681	0,926671
	Skandinaviska Enskilda Banken AB	0,000365	0,030059	11,352509	0,652001
	Svenska Handelsbanken AB	0,000458	0,021166	6,866941	0,551787
	Swedbank AB	0,000298	0,029367	7,492763	0,242297
UK	Royal Bank of Scotland Group plc	-0,000428	0,040844	58,054038	-2,34447
	HSBC Holdings plc	0,000119	0,019237	16,126945	0,172958
	Barclays plc	0,000414	0,038612	85,578023	4,365352
	Lloyds Banking Group plc	0,000085	0,038292	35,761418	0,876582

4.2 Results from diagnostic testing

The squared returns have been tested for autocorrelation through a Ljung-Box test. All of the 25 banks showed strongly significant evidence of autocorrelation which is relevant for suggesting a GARCH (1, 1) model. When estimating a GARCH (1, 1) model for the 25 banks some conditions must be fulfilled. The ARCH-parameter should take a value between 0 and 1, the same condition for the GARCH-parameter and the sum of the ARCH-parameter and the GARCH-parameter cannot exceed 1. If the sum of the ARCH-parameter and the GARCH-parameter becomes 1, it is an indication of unit root in the conditional variances. Therefore have two different unit root tests been run; the Augmented Dickey Filler test and the Phillips Perron test which did not show any sign of unit root in the conditional variances series.

4.3 Results from the GARCH (1, 1) model

The GARCH models have been estimated on daily data that have been converted into monthly data in order to reduce noise. In the table below the parameter values are given for each of the 25 banks and those which fulfilled the conditions of a GARCH (1, 1) are marked with stars in the column to the right. As can be seen they all show highly significant parameter values. For the rest whose sum of the ARCH-parameter and the GARCH-parameter became 1, although tests have been done, is an indication of non-stationarity in the conditional variances. Therefore an Integrated GARCH (1, 1) model was fitted instead. The results for those 10 banks are shown in table 3. For the GARCH (1, 1) model the GARCH-parameter is quite high for most of the banks which indicates that volatility is persistent and takes a long time to change. For the banks modeled with the GARCH (1, 1) model only five banks have an ARCH-parameter value over 0.10, although they are not over 0.2 and it can still be stated that they are quite small. The R^2-values are extremely small which is common in high frequency financial data since a R^2-value near zero indicates that stock returns are close to unpredictable. This also proves the underlying assumption of efficient markets that is made in Hall and Miles (1990).

Table 2. Results from the GARCH (1,1) model

	Constant	Signif. level	ARCH	Signif. Level	GARCH	Signif. Level	GARCH (1,1)	R^2
Erste Bank Group	0,001001	**	0,074965	***	0,919974	***	*	-0,000251
KBC Bank	0,000003	***	0,095912	***	0,907355	***		
Danske Bank	0,000006	***	0,180983	***	0,821055	***		
BNP Paribas	0,000003	***	0,102941	***	0,896551	***	*	-0,000103
Credit Agricole	0,000004	***	0,084437	***	0,913515	***	*	-0,000169
Societe Generale	0,000004	***	0,144579	***	0,861986	***		
Deutsche Bank	0,000004	***	0,084517	***	0,909588	***	*	-0,000387
Commerzbank	0,000005	***	0,062932	***	0,929660	***	*	-0,001083
Allied Irish Banks	0,000001	**	0,125379	***	0,891361	***		
Unicredit	0,000002	***	0,127587	***	0,878126	***		
Banco Popolare	0,000004	***	0,086216	***	0,908680	***	*	-0,001549
Banca M. D. P.	0,000008	***	0,097671	***	0,882476	***	*	-0,001254
UBI Banca	0,000002	***	0,062131	***	0,930745	***	*	-0,000905
Banco Com. Portugues	0,000010	***	0,166580	***	0,823446	***	*	-0,004074
Banco Santander	0,000005	***	0,163244	***	0,835424	***	*	-0,000618
Banco Popular Espan.	0,000002	***	0,100637	***	0,901478	***		
Banco Pastor	0,000005	***	0,092613	***	0,897042	***	*	-0,001203
Nordea Bank	0,000004	***	0,084825	***	0,907890	***	*	-0,000300
SEB	0,000005	***	0,119472	***	0,877902	***	*	-0,000575
SHB	0,000004	***	0,111545	***	0,882871	***	*	-0,000192
Swedbank	0,000003	***	0,090864	***	0,906878	***	*	-0,000590
RBS	0,000004	***	0,131384	***	0,875303	***		
HSBC	0,000001	***	0,093219	***	0,908788	***		
Barclays	0,000006	***	0,173784	***	0,835303	***		
Lloyds	0,000001	***	0,126256	***	0,877550	***		

* significant at a 10-% level,
** significant at a 5-% level,
*** significant at a 1-% level

4.3 Results from the IGARCH (1, 1) model

The results from the IGARCH (1, 1) model show that most of the parameters are significant. Only one bank, Danske Bank has an ARCH-parameter value higher than 0.10 which indicates that the volatility is persistent in the general case even for the IGARCH (1, 1) model. The R^2-value for the banks modeled with the IGARCH (1, 1) is, as in the GARCH (1, 1) model very close to zero indicating the challenge in predicting stock returns.

Table 3. Results from the IGARCH (1, 1) model

	Constant	Signif. level	ARCH	Signif. level	IGARCH (1,1)	Signif. Level	R^2
KBC Bank	0,001013	***	0,065934	***	0,934066	***	-0,000181
Danske Bank	0,000653	**	0,180983	***	0,821055	***	-0,000129
Societe Generale	0,000789	***	0,090218	***	0,909782	***	-0,000557
Allied Irish Banks	0,000807	***	0,072100	***	0,927900	***	-0,000796
Unicredit	0,000637	***	0,078636	***	0,921364	***	-0,000554
Banco Popular Espan.	0,000429	**	0,066656	***	0,933431	***	-0,000873
RBS	0,000564	***	0,062261	***	0,937739	***	-0,000591
HSBC	0,000196	-	0,065400	***	0,934600	***	-0,000016
Barclays	0,000420	-	0,107890	***	0,892110	***	0,000000
Lloyds	0,000166	-	0,080578	***	0,919422	***	-0,000005

4.4 Correlation between 1/σ and the CDS spreads

In the table below the correlation coefficients are presented between the default measure 1/σ from GARCH (1, 1) and IGARCH (1, 1) respectively, and the CDS spreads. From theory, the correlation coefficient should go towards -1 which is seen for most of the banks. As many as 10 banks have a correlation coefficient that is lower than -0.8 which indicates that for those banks, theory is well applied in practice. Two banks; Banco Pastor and Banco Comercial Português differ quite much from the rest and exhibit weak correlation between the 1/σ measure and the CDS spreads.

Table 4. Correlation between 1/σ and the CDS spreads

	Correlation between 1/σ and CDS spreads
Erste Bank Group	-0,839314
KBC Bank	-0,799645
Danske Bank	-0,741812
BNP Paribas	-0,824805
Credit Agricole	-0,834141
Societe Generale	-0,818424
Deutsche Bank	-0,866534
Commerzbank	-0,726251
Allied Irish Banks	-0,701900
Unicredit	-0,711055
Banco Popolare	-0,669726
Banca M. D. P.	-0,694378
UBI Banca	-0,822053
Banco Com. Portugues	-0,505422
Banco Santander	-0,814261
Banco Popular Espan.	-0,748030
Banco Pastor	-0,397532
Nordea Bank	-0,819347
SEB	-0,701851
SHB	-0,697863
Swedbank	-0,654014
RBS	-0,841180
HSBC	-0,843850
Barclays	-0,825360
Lloyds	-0,793770

From the diagrams in the appendix we can see the plotted series for the 1/σ measure on the left hand side and the CDS spreads on the right hand side for each of the 25 banks. In general, the default measure based on stock prices is much more volatile than the CDS spreads during the entire time period. The 1/σ measure presents clearly high values in the beginning of the period and a decreasing trend towards the end of the period. Most banks indicate a peak around December 2006 and a following dip around December 2008. Since then most of the banks show an upward trend, although quite volatile. A low value of the default measure based on stocks indicates a high risk of default while a high value of the default measure indicates a more stable period. In absolute terms, the banks that have been under 10 since the dip in the beginning of the financial crisis and that have only barely recovered back to above 10 are; Erste Bank Group, KBC Bank, Crédit Agricole, Allied Irish Group, Unicredit, The Royal Bank of Scotland and Lloyd Banking Group. Only Commerzbank, Banco Pastor and HSBC Holdings seem to be on a slowly upward trend since the plunge while for the rest of the banks a smaller plunge around June 2010 delayed the recovery path from the financial crisis.

Looking at banks which originate from the same country, starting with France, the three banks BNP Paribas, Crédit Agricole and Société Générale seem to have behaved quite similarly before, during and after the financial crisis. The two banks established in Germany seem also to have behaved quite similarly. The four Italian banks Banca M.D.P di Siena and UBI Banca show quite a similar pattern in a higher tendency of recovering than Unicredit and Banco Popolare. However, all of the four banks had a plunge around June 2010 which was relatively deeper for Banca M.D.P di Siena and UBI Banca than for the other two. The Spanish banks do not show such a clear pattern since they all behave very volatively which makes it difficult to draw any conclusions regarding them. Especially Banco Pastor exhibits a very volatile pattern which makes it almost impossible to interpret the results. Three of the Swedish banks; Nordea Bank, Skandinaviska Enskilda Banken och Svenska Handelsbanken appear to have recovered better from the financial crisis than Swedbank. The three banks had a higher peak after the crisis and not such as deep decline in June 2010 as Swedbank had. The four banks established in the United Kingdom indicate a common pattern where the banks were deeply affected by the financial crisis and have all recovered slowly.

From looking at the CDS spreads one clear pattern is noticed; almost nothing happened before June-December 2007 and after that the market and trade with CDS have exploded which explains the very low spreads before the crisis and the larger ones during the crisis. For most banks the spread levels went down to levels around 100-250 at the end of the crisis but there are exceptions. For Allied Irish Group, Banco Comercial Português, Banco Popular Español and Banco Pastor large spreads around 300-400 are still present even after the crisis. There are also exceptions of banks that had relative lower spreads after the crisis than the rest. Six banks have come back to spread levels below 100. Of these six are four of them Swedish, one from Denmark and one from The United Kingdom.

4.5 Rankings from Standard & Poor's

Although the purpose of this thesis is not to compare the default measures with credit ratings from rating agencies a small comparison is made, however not with the intention of comparing the different ratings with the 1/σ measure or the CDS spreads. I will instead focus on when the latest ratings were made and compare it to the movements after that of the two measures in this study. Hence, due to difficulties when downloading the CDS data from Datastream I had to chose data-series that ended 30 September 2010, if I had been able to collect data until today this part of the study had been more comprehensive. Still, only four of the 25 banks had their ratings changed after 30 September 2010; Crédit Agricole, Allied Irish Banks, Banco Comercial Português and Banco Popular Español. Looking at the default measure 1/σ and the CDS spreads we can see that these four banks were either one of those which had very low 1/σ value during the crisis or had a very high CDS spread even after the crisis. Except for the actual rating changes Standard & Poor's also announce outlooks, an early indication of a possible change in a bank's credit rating. Except for the four banks that had an actual change in their credit rating, two more banks had this indication of a change; Erste Bank and Banco Popolare. For most of the banks they had their credit rating either changed or an outlook during 2009 or 2010. What is interesting to notice is that two of the Swedish banks; Nordea Bank and Svenska Handelsbanken seem to, according to the ratings by Standard & Poor's not been affected enough according to have a change in their rating of their financial strength. Although these two banks seem to, by looking at the default measure 1/σ and the CDS spreads, have recovered quite well the market's view of credit strength have changed extremely during the financial crisis.

5. Conclusions

Employing a simplified measure based on the Hall and Miles (1990) approach using stock prices in comparison to CDS spreads, the health of the European banking sector during the years 2004 to 2010 have been investigated. From the individual GARCH (1, 1) and IGARCH (1, 1) models the significant results indicate that conditional variances add information in predicting returns. According to underlying theory calculations on the correlation between the two default measures should go towards -1 which is true for most of the banks. From the diagrams for each of the 25 banks we can see a peak before the financial crisis and a following plunge in the default measure based on stock prices while the opposite is true for the CDS spreads where almost nothing happened before the crisis to suddenly explode of high spreads during the crisis. From the two default measures together we can conclude that five banks have been more affected than the rest; Allied Irish Group, Crédit Agricole, Banco Comercial Português, Banco Popolare Español and Banco Pastor. Of these five, two are from Spain and the rest from France, Portugal and Ireland. The six banks that have, according to these measures, been the least affected by the financial crisis are Nordea Bank, Skandinaviska Enskilda Banken, Svenska Handelsbanken, HSBC Holdings, Deutsche Bank and Commerzbank where three of them are established in Sweden, one in The United Kingdom and two in Germany.

From the small comparison to credit ratings by the rating agency Standard & Poor’s, their rating changes seem to be on the same banks that have been the most affected by the crisis according to the default measures. Hence, according to Standard & Poor’s some banks have not had their rating changed since before the crisis although, according to our default measures, we can see that those banks have had both peaks and declines during the same period. What the default measure explains, since it is based on market data is a point-in-time measure of default. Would then a point-in-time measure harm the banking sector by creating insecurity in the banking sector by constantly changing? The results should not be an indication of causing more insecurity, a constant changing default measure would instead be a more honest system since no subjectivity lies within the measure and the discussion whether it was right or wrong to change a credit rating on a company, loan or a sovereign state would not be an issue.

For further research I would find it interesting to study the CDS market in the United States during the time period for the downgrade of the sovereign state by Standard & Poor’s. Since the major drawback of the default measure based on stock prices is the absence of predicting default for sovereign states and other institutions that are not represented at the stock market it would be interesting to further develop measures such as CDS. It would also be interesting to develop a more advanced measure where actual probabilities of default can be calculated.

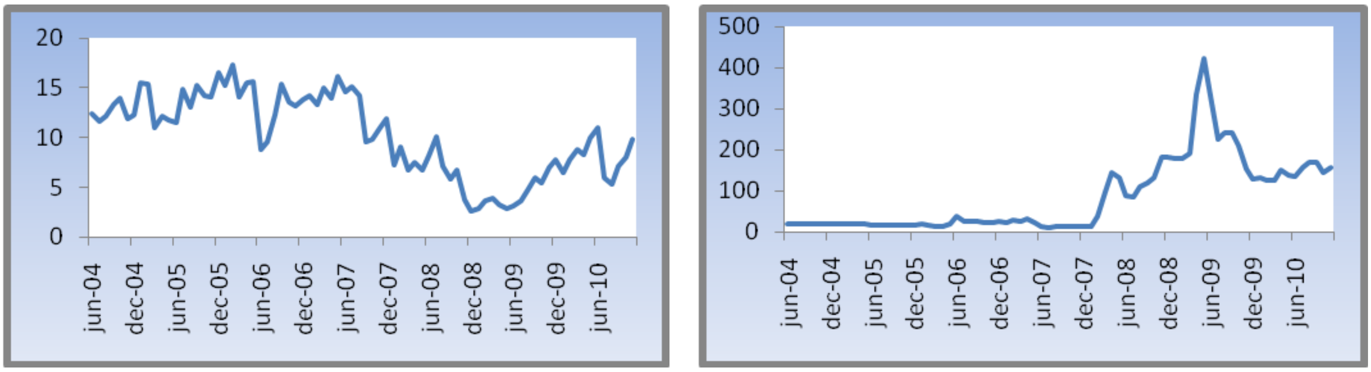
Appendix

Table 5. Results from diagnostic testing

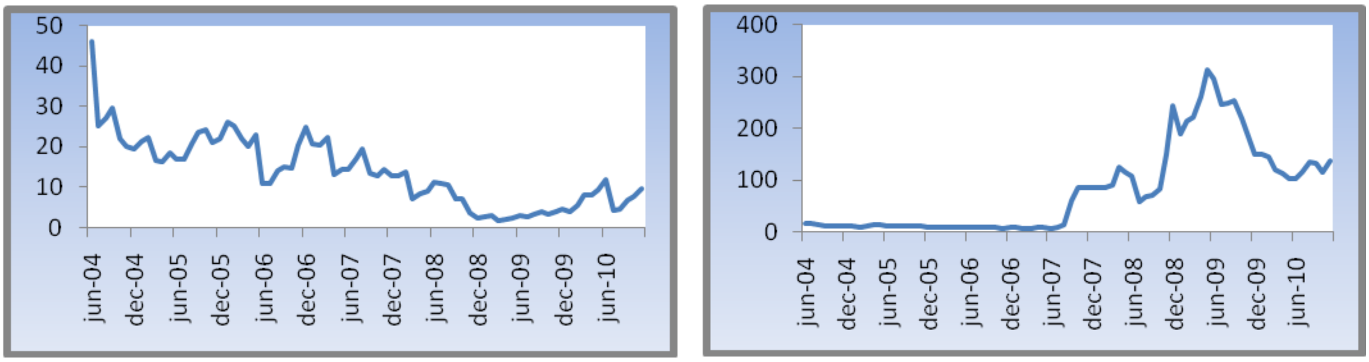
	Ljung-Box autocorrelation exists	Unit root ADF GARCH(1,1)	Unit root reject	Unit root ADF IGARCH (1,1)	Unit root reject	Phillips-Perron Unit root reject
Erste Bank Group	***	-2,772245	*	Not tested	-	*
KBC Bank	***	-6,005321	***	-4,815526	***	***
Danske Bank	***	-6,290181	***	-3,786595	***	***
BNP Paribas	***	-4,404797	***	Not tested	-	***
Credit Agricole	***	-3,362403	**	Not tested	-	***
Societe Generale	***	-5,512345	***	-4,253054	***	***
Deutsche Bank	***	-3,447681	***	Not tested	-	***
Commerzbank	***	-3,518122	***	Not tested	-	**
Allied Irish Banks	***	-5,160650	***	-4,199634	***	***
Unicredit	***	-4,275276	***	-3,944426	***	***
Banco Popolare	***	-4,731331	***	Not tested	-	***
Banca M. D. P.	***	-5,983332	***	Not tested	-	***
UBI Banca	***	-3,121681	**	Not tested	-	**
Banco Com. Portugues	***	-8,400109	***	Not tested	-	***
Banco Santander	***	-6,046117	***	Not tested	-	***
Banco Popular Espan.	***	-4,899133	***	-3,541013	***	***
Banco Pastor	***	-5,741400	***	Not tested	-	***
Nordea Bank	***	-3,317066	**	Not tested	-	**
SEB	***	-4,209951	***	Not tested	-	***
SHB	***	-3,534213	***	Not tested	-	***
Swedbank	***	-3,360810	**	Not tested	-	**
RBS	***	-6,860664	***	-4,919326	***	***
HSBC	***	-3,991177	***	-3,545642	***	***
Barclays	***	-9,261566	***	-6,916601	***	***
Lloyds	***	-3,615291	***	-3,777455	***	***

* significant at a 10-% level,
** significant at a 5-% level,
*** significant at a 1-% level

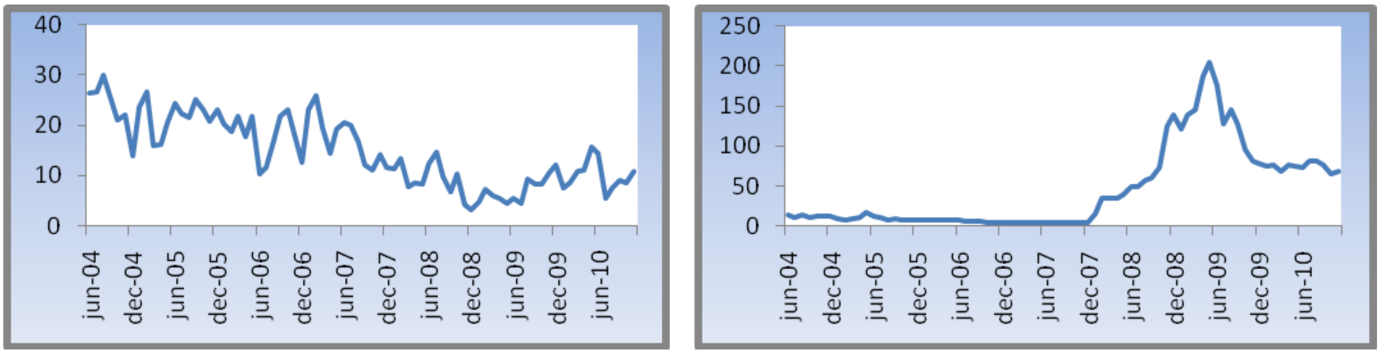
Diagrams presenting the correlation between the 1/σ measure and the CDS spreads



Erste Bank Group



KBC Bank



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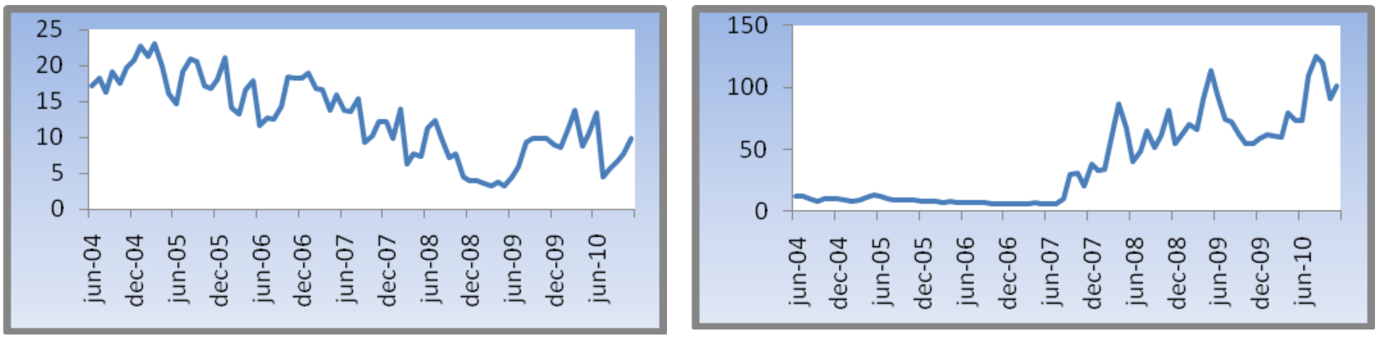

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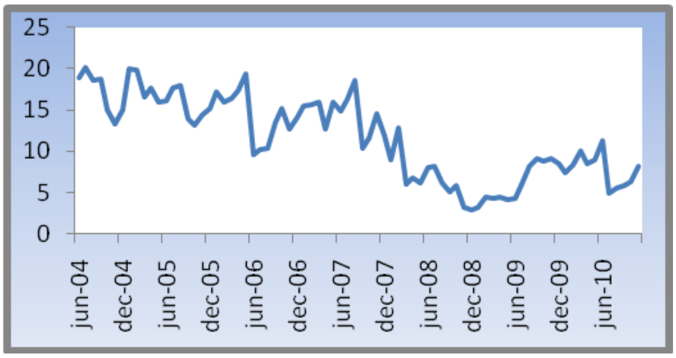
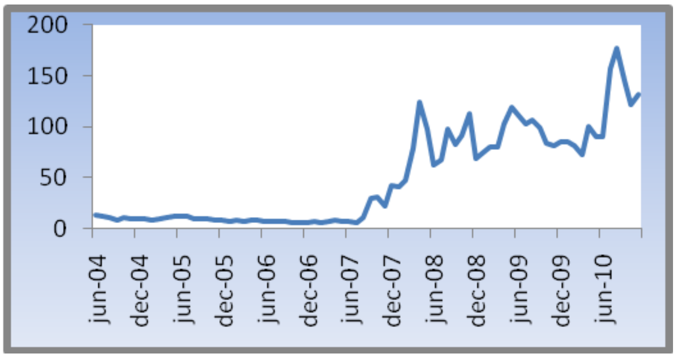
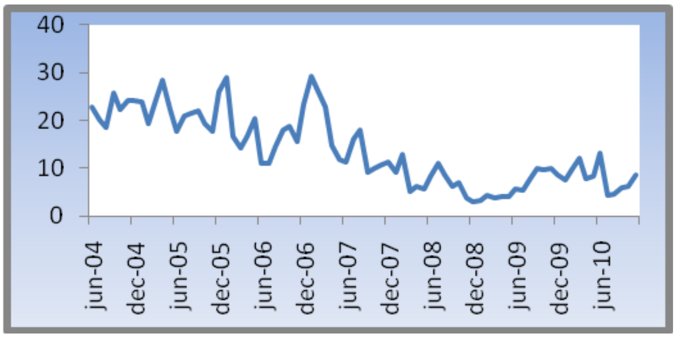
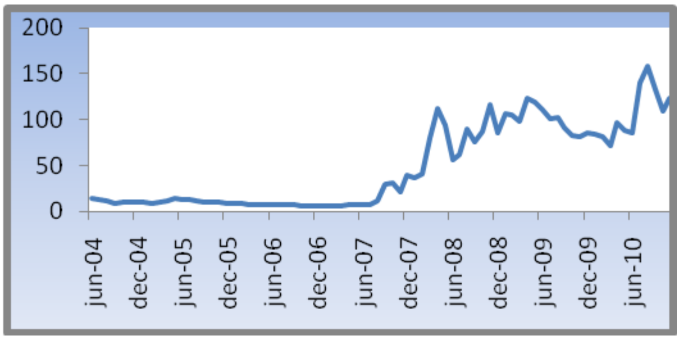




Crédit agricole





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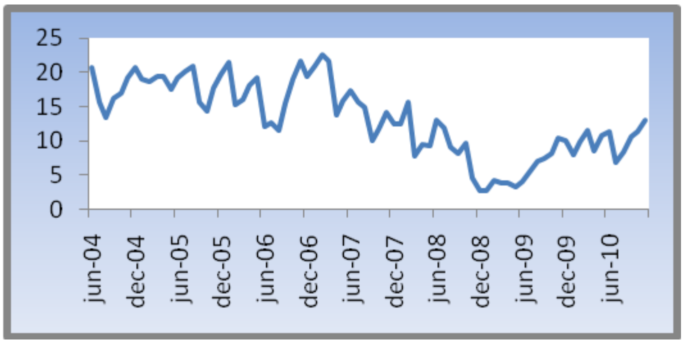

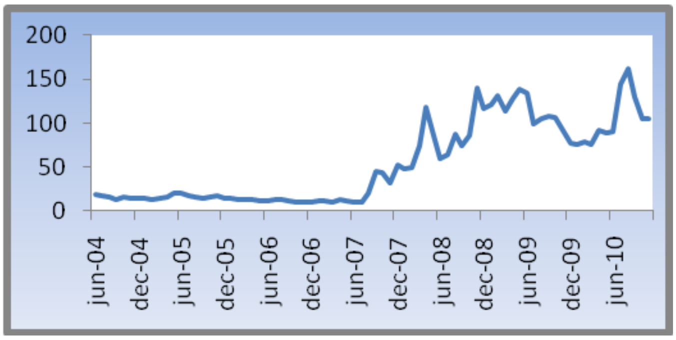

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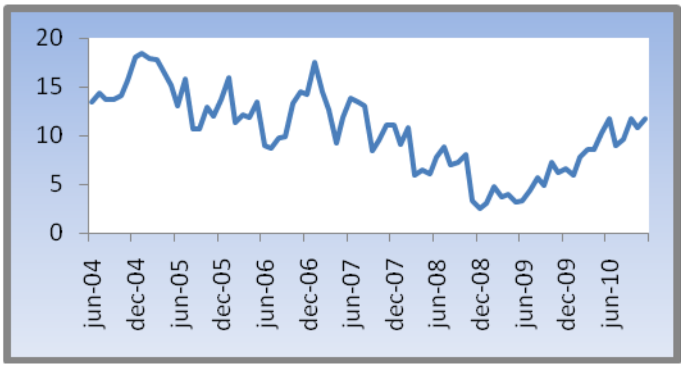

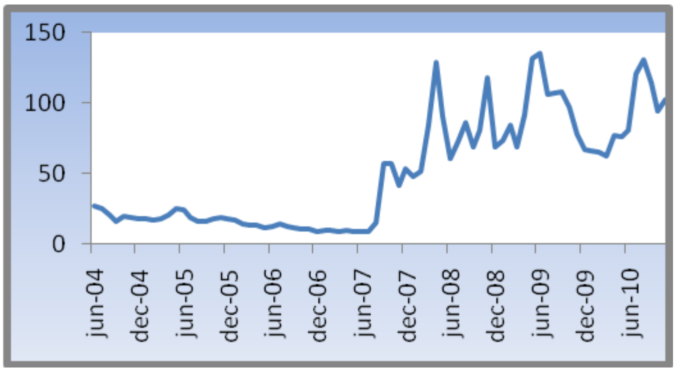

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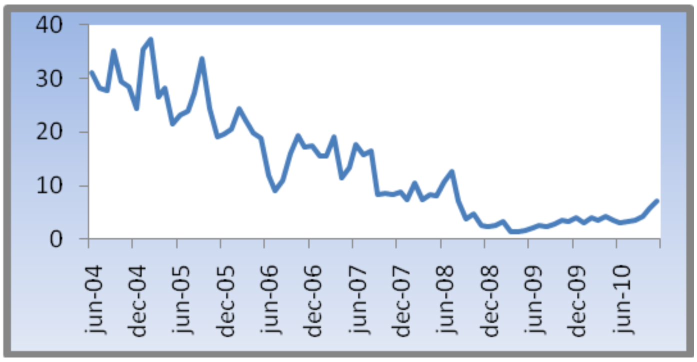
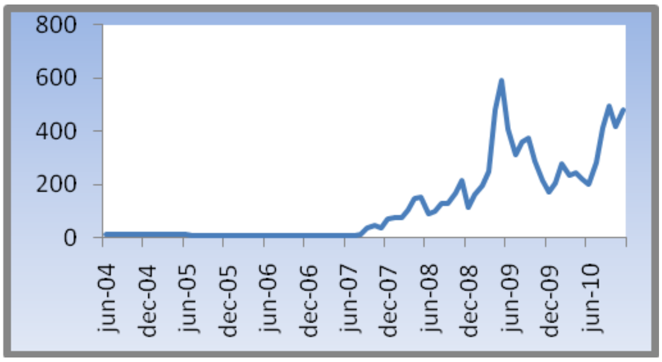
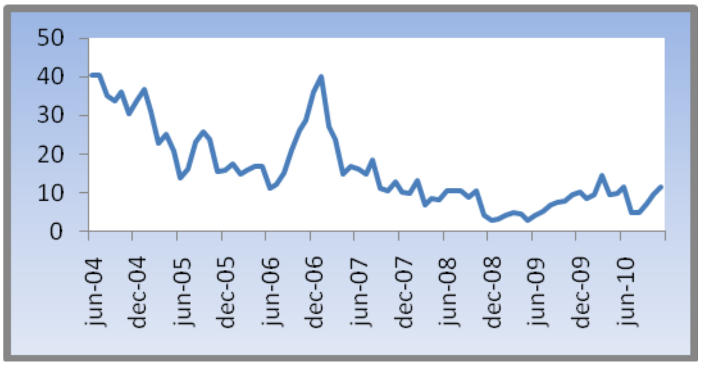
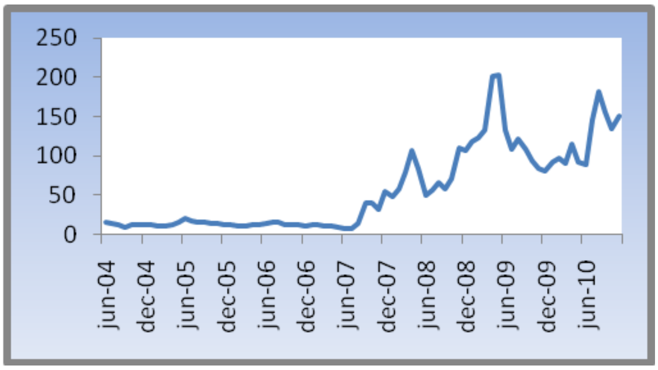




Allied Irish Group





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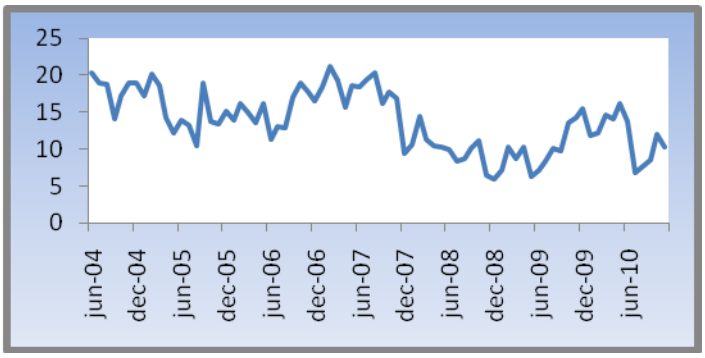
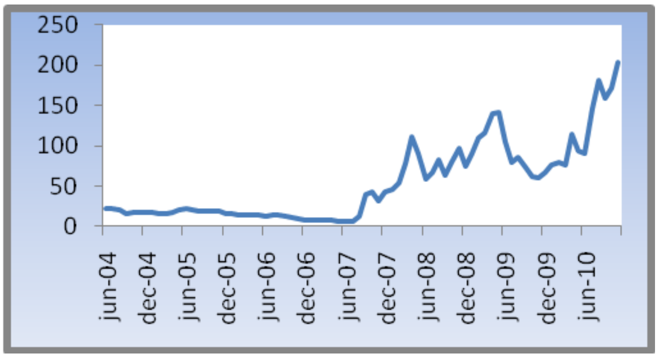
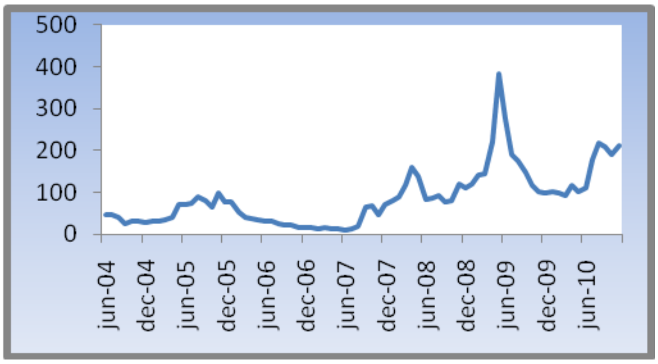




Banca M.D.P. di Siena



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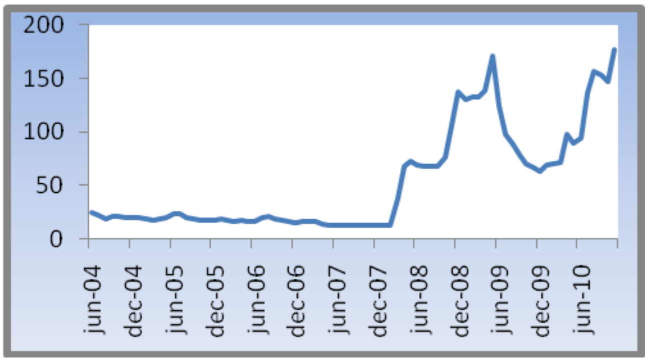

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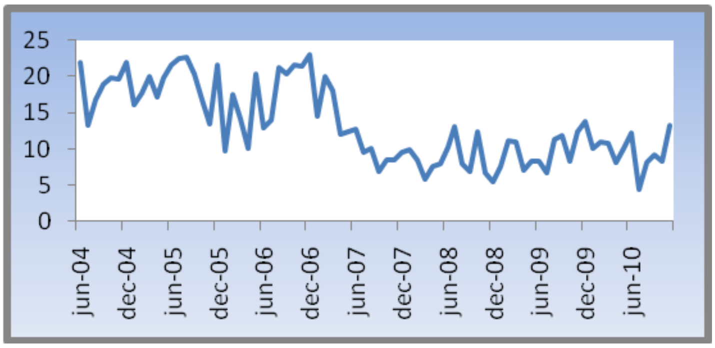

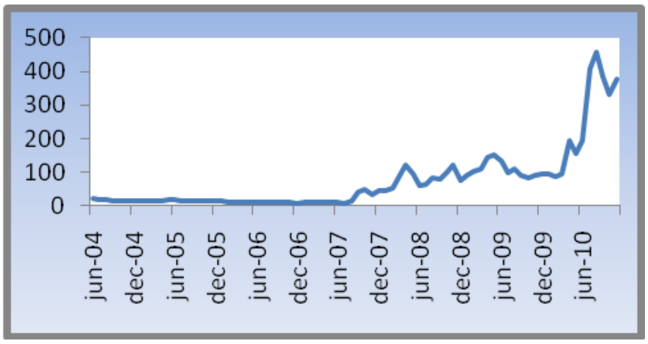

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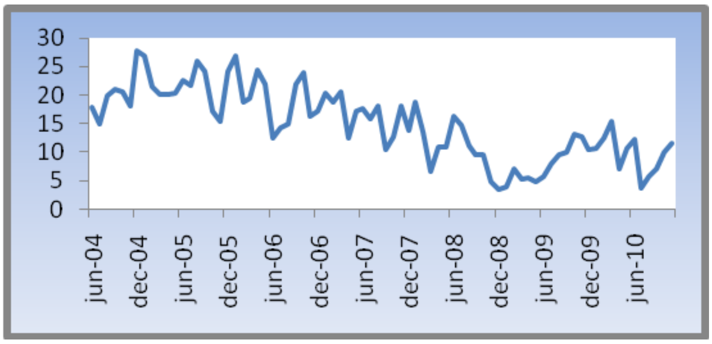

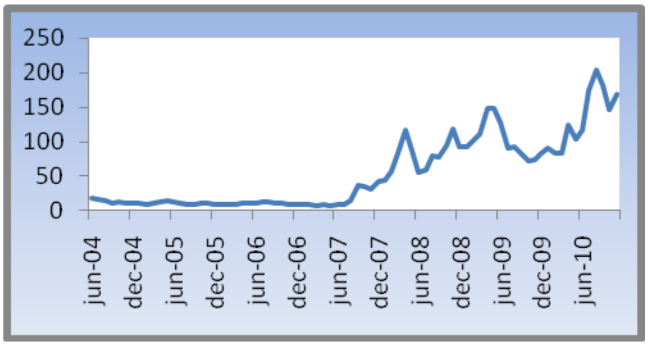

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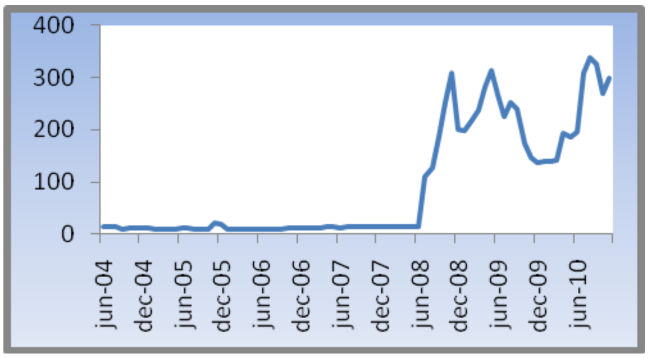

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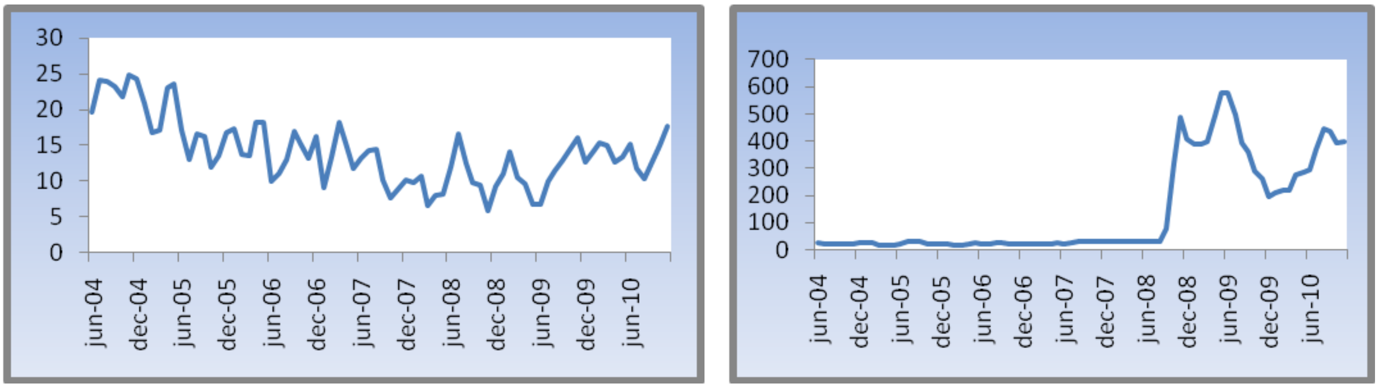
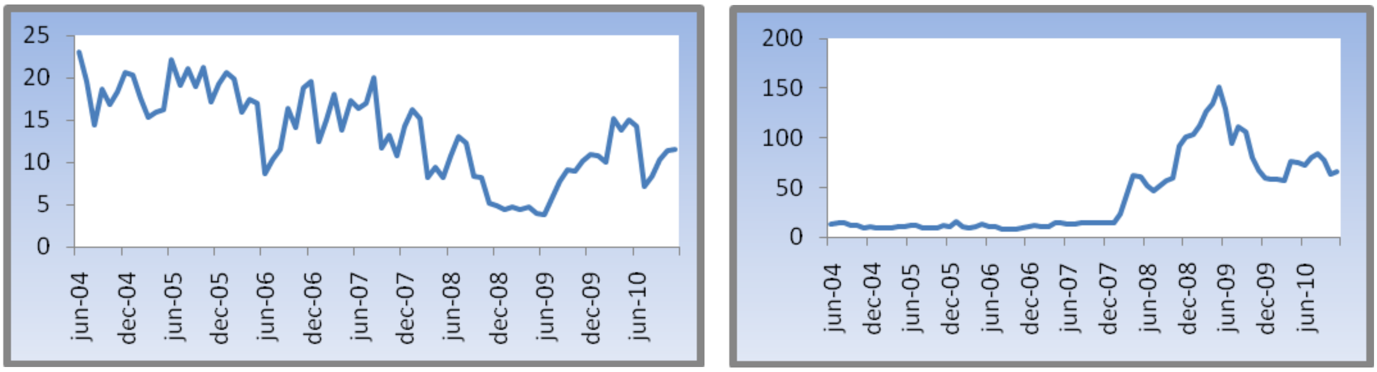
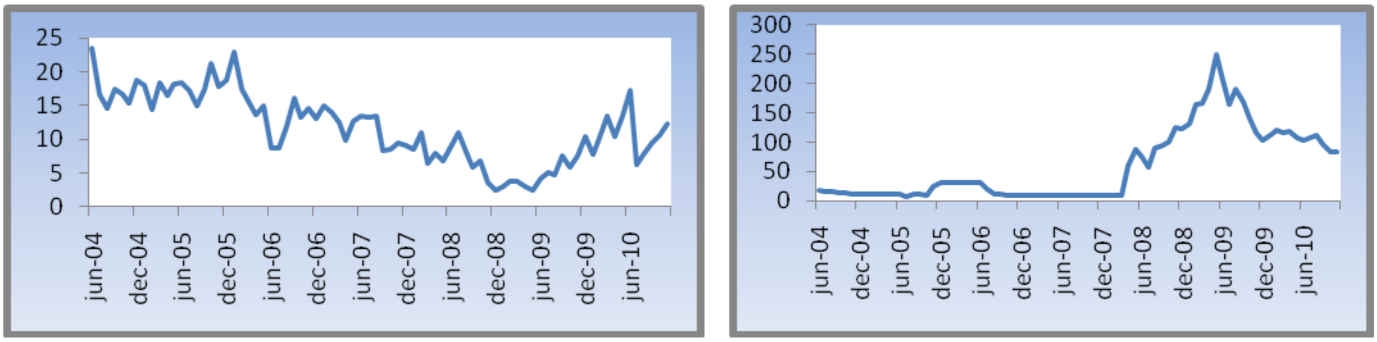


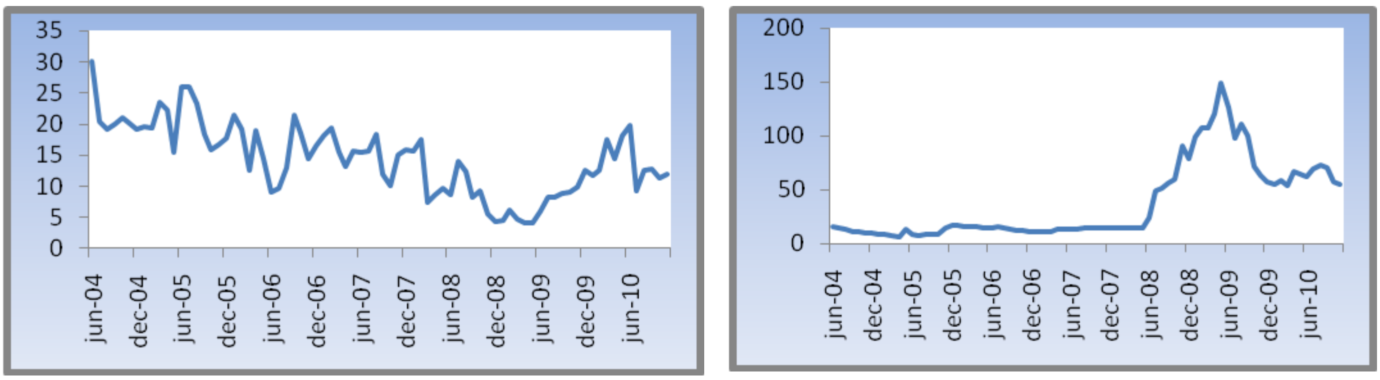
Banco Pastor



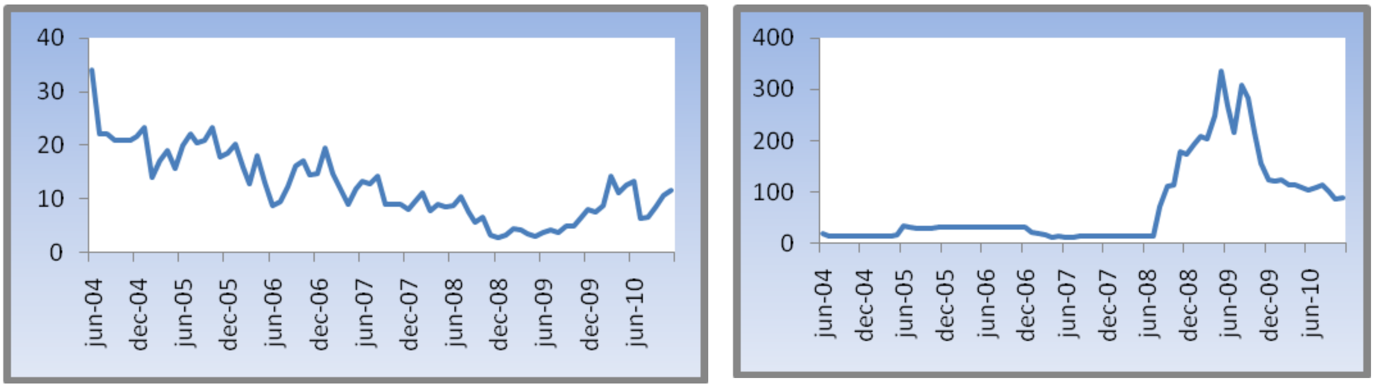
Nordea Bank



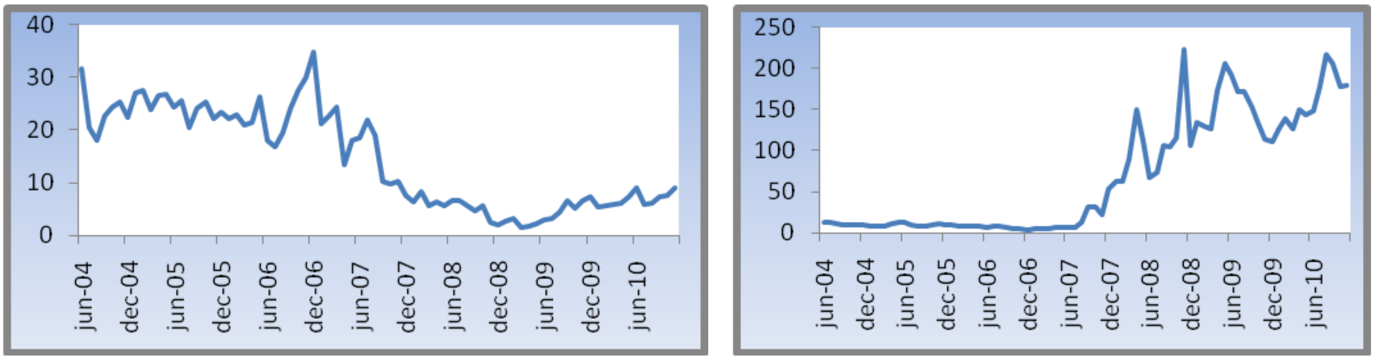
Skandinaviska Enskilda Banken



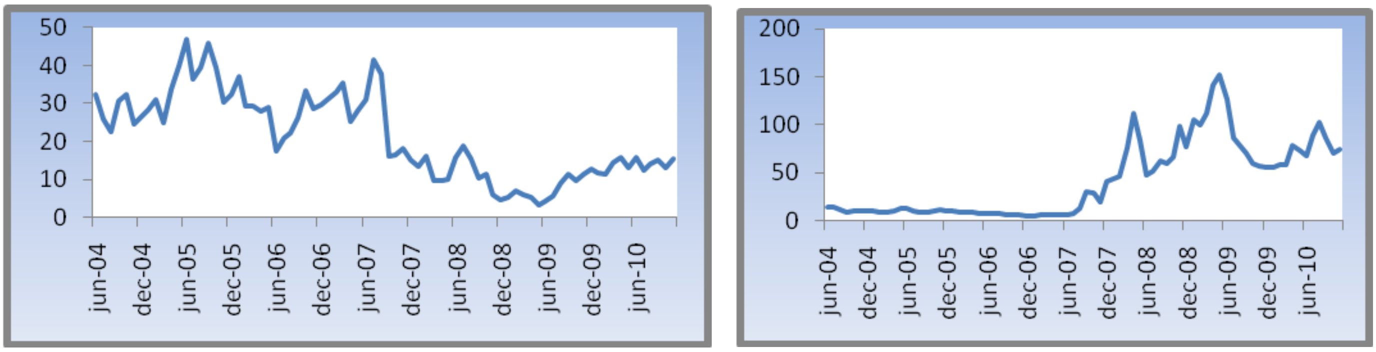
Svenska Handelsbanken



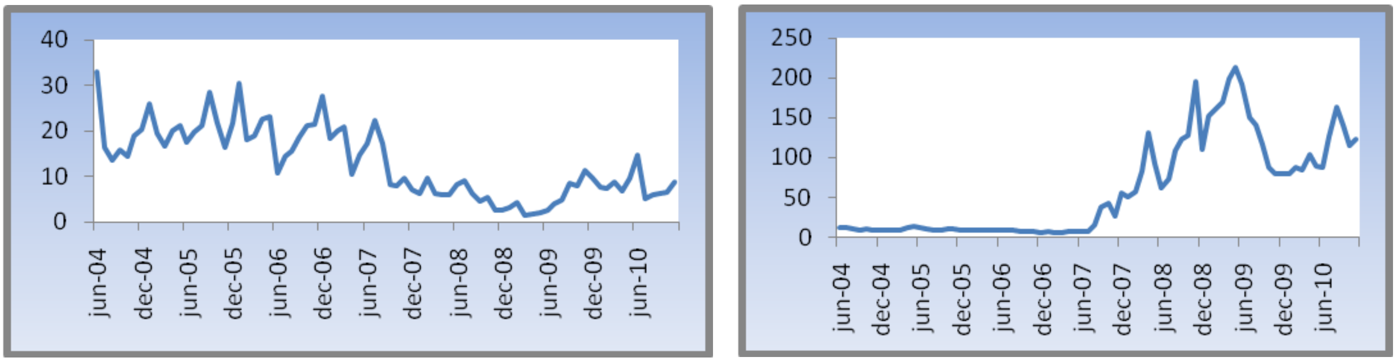
Swedbank



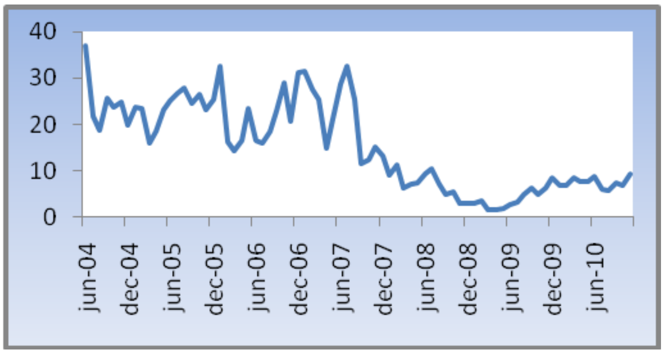
The Royal Bank of Scotland

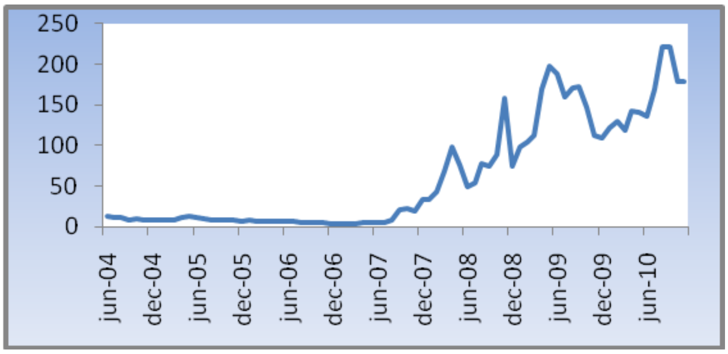


HSBC Holdings



Barclays





Lloyd Banking Group

Table 6. Rankings from Standard & Poor's

Bank	Foreign Long Term	Foreign Short Term	Local Long Term	Local Short Term	Latest updated	Outlook
Erste Bank Group	A	A	A	A	05 Dec 2006	24 Nov 2010
KBC Bank	A	A	A	A	18 Mar 2009	18 Mar 2009
Danske Bank	A	A	A	A	18 Dec 2009	18 Dec 2009
BNP Paribas	AA	A	AA	A	28 Jan 2009	28 Jan 2009
Credit Agricole	A	A	A	A	20 May 2011	20 May 2011
Societe Generale	A	A	A	A	07 May 2009	07 May 2009
Deutsche Bank	A	A	A	A	19 Dec 2008	19 Dec 2009
Commerzbank	A	A	A	A	22 Mar 2007	12 May 2009
Allied Irish Banks	BB	B	BB	B	02 Feb 2011	11 Jul 2011
Unicredit	A	A	A	A	18 Mar 2009	18 Mar 2009
Banco Popolare	A	A	A	A	22 Jul 2004	06 May 2011
Banca M. D. P.	A	A	A	A	01 Oct 2009	01 Oct 2009
UBI Banca	A	A	A	A	05 Mar 2007	23 Apr 2010
Banco Com. Portugues	BBB	A	BBB	A	28 Mar 2011	11 Jun 2011
Banco Santander	AA	A	AA	A	07 Mar 2007	04 Mar 2009
Banco Popular Espan.	A	A	A	A	22 Feb 2011	22 Feb 2011
Banco Pastor	-	-	-	-	-	-
Nordea Bank	AA	A	AA	A	29 Nov 2005	29 Nov 2005
SEB	A	A	A	A	05 Feb 2009	23 Feb 2010
SHB	AA	A	AA	A	11 Nov 2004	11 Nov 2004
Swedbank	A	A	A	A	03 Oct 2008	23 Feb 2010
RBS	A	A	A	A	19 Dec 2008	19 Dec 2008
HSBC	AA	A	AA	A	19 Jun 2006	20 Aug 2010
Barclays	AA	A	AA	A	19 Dec 2008	19 Dec 2008
Lloyds	A	A	A	A	06 Mar 2009	06 Mar 2009

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