Estimating Default Probabilities Using Stock Prices: The Swedish Banking Sector During the 1990s Banking Crisis

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Abstract

The growing interest in management of credit risk and estimation of default probabilities has given rise to a range of more or less elaborate credit risk models. Hall and Miles (1990) suggests an approach of estimating failure probabilities based solely on stock market prices. The approach has the advantage of simplicity but relies on market efficiency to hold. In this paper we suggest an extension to the Hall and Miles (1990) model using extreme value theory and apply the extended model to the Swedish financial sector and to individual Swedish banks. The 15-year long sample in our study covers the period of the Swedish banking crisis of the early 1990s. We find a close correspondence between changes in the estimated probabilities of failure and the actual credit events occurring. Credit ratings from major credit rating agencies, on the other hand, are shown to react much less and much slower to credit quality changes.

Keywords: banking crisis; default; credit risk; extreme value theory
JEL classification codes: G33; G14; G21; C32

1 Introduction

The health of the banking sector is of crucial importance to the functioning of a modern market economy and banks and other financial institutions are therefore closely monitored by governments, supervisors, and regulators. Typically, supervisors use rather traditional approaches to monitor the banks. They can for instance rely on (private) rating agencies that rate individual banks' capability of servicing and repaying their obligations[1]. They can also rely on scoring models that attempt to assess the probability of default using accounting information supplied by the banks themselves. Although useful, the rating approach as well as the accounting information based models have some major drawbacks. When it comes to traditional rankings from rating agencies the most obvious drawback is their infrequent updating (perhaps once or twice a year). In addition, for non-US banks (the US is the home of most rating agencies) the ratings are of much lower quality. Accounting based models, on the other hand, are based on data that not only is updated with a rather low frequency, as well as released with a time lag, but also suffers from possible accounting manipulations due to agency problems between the bank and the supervisor. In addition, accounting information is inherently backward looking, based on historic information rather than the market's assessment of the future.

In an attempt to more accurately predict failures of firms (which is of interest to both supervisors and the banks themselves) much effort has been invested in the development of new models of default probabilities that uses finance theory and market data in addition to accounting data. Many of these models are so called structural models based on the seminal Black and Scholes (1973) and Merton (1974) papers; the most well known application being the KMV^{TM} model (KMV (1997))[2]. A problem with these approaches, however, is their proprietary nature; they rely on private databases of defaulted and non-defaulted firms and are not possible to implement by outsiders. In addition, they are less suitable for financial firms and banks due to these institutions' high leverage and opaque balance sheets.

There have also been some attempts to use stock prices more directly as indicators of changes in banks' financial conditions. One such study is Shick and Sherman (1980) that investigates bank stock prices and their ability to function as an "early warning system". Shick and Sherman (1990) finds that changes in regulator ratings of a certain bank are reflected in the behavior of the bank's stock price and that the stock price corrections lead the actual rating change by at least 15 months. An other study that examines the ability of stock prices, stock return volatilities as well as other market variables in predicting rating changes is Curry, Elmer and Fissel (2001).

[1] Moody's, and Standard&Poor are some of the better known rating agencies.

[2] Recently, both Moody's and Standard&Poor have developed corresponding models and in February 2002 Moody's bought KMV.

Investigating a large number of banks that have faced changes in their regulator rating they find that stock prices keep falling and stock return volatilities keep raising for at least a year before the actual downgrading occurs. The major drawbacks of these studies are their purely statistical nature and that they do not rest on theoretical grounds; there is no model underneath that motivates the different market variables as being important as default probability measures.

To avoid the problems mentioned, we have chosen to adopt an approach suggested by Hall and Miles (1990). This approach relies solely on stock market data and can therefore be used on any bank or company with traded stocks. It is also easily reproduced by anyone who has access to the history of stock prices of the company in question. The Hall and Miles (1990) approach is not without its own drawbacks and a major assumption is that the efficient market hypothesis is expected to hold (just as in the Merton (1974) approach). By relying on markets to be efficient, the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965), and a modelling of returns as Generalized Autoregressive Conditional Heteroscedastic in Mean (GARCH-M) processes, the Hall and Miles (1990) approach gives us a measure of the distance to default of a particular bank at its current stock price and current stock price volatility. This distance to default measure can then easily be transformed to a failure (default) probability[3].

In order to assess the performance of the Hall and Miles (1990) approach, Clare and Priestly (2002) applies the approach to the Norwegian banking sector and calculate the probability of failure of this sector. In the late 1980s the Norwegian banking sector underwent a period of serious trouble with a number of banks going bankrupt or being rescued by the government and Clare and Priestley (2002) shows that the market based approach of Hall and Miles (1990) captures much of this turmoil by indicating an increased probability of bank default during the crisis years compared to before/after the crisis.

In this paper we apply an extended, extreme value theory (EVT), version of the Hall and Miles (1990) approach to the Swedish banking sector, and compared to Hall and Miles (1990) and Clare and Priestley (2002) we also try to be more systematic in our choice of model specification. In order to assess the sensitivity of the approach to different model specifications we try different (standard) specifications and data frequencies. We then apply the model to a 15-year long sample covering the three major Swedish banks (Nordbanken, Skandinaviska Enskilda Banken and Svenska Handelsbanken)[4] and the major Swedish financial index (Veckans Affär-

[3] In this paper we use the words default and failure as synonyms indicating the point when equity holders, and some debt holders, looses all, or large parts of, its invested capital.

[4] These names are the most representative for the whole period. In 1997 Nordbanken merged with Merita Bank, and changed name to MeritaNordbanken. In 2000 MeritaNordbanken merged with Unidanmark, and in 2001 they changed their name to Nordea. Skandinaviska Enskilda Banken goes under the name SEB since 1998, and Svenska Handelsbanken is often simply called Handelsbanken.

ers Bank&Finance Index) around the Swedish banking crisis in the early 1990s. Compared to Hall and Miles (1990) and Clare and Priestley (2002), we present our results in a more useful and informative way by transforming the model's default measure to an actual probability of default. This presentation also has the advantage of facilitating a comparison of our estimated default rates with those from credit rating agencies (we compare our probabilities with those from Fitch and Moody's). Finally, while both Hall and Miles (1990) and Clare and Priestley (2002) ignore the well known fact of fat-tailed stock return distributions by assuming a normal loss distribution, we use extreme value theory to get the default probabilities.

We find that, according to the stock market, failure probabilities of Swedish banks increased significantly during the crisis years, and, even though the relative ranking of different banks was the same according to the market and according to the rating agencies, when we compare the actual probabilities of failure using the market model with those from rating agencies we find large differences. The rating agencies downgraded the major Swedish banks in the wake of the crisis but not to levels even close to that perceived as appropriate by the stock market. Partly, this is certainly due to the rating agencies' focus on creditors, and the possibility of a government bail out reducing the probability of the bank actually defaulting on its bonds and loans. Nonetheless, the small and rather delayed corrections of the ratings, if any, contain very little information about the intrinsic financial strength of the bank. The stock market, on the other hand, reacts very fast to changes in the intrinsic health of the bank.

Finally, the choice of loss distribution (normal or fat-tailed (EVT)) is found to be most critical in tranquil periods when the probability of default is small. During the crisis there is no significant difference in implied default probability.

The paper is organized as follows: section 2 gives an introduction to the Swedish banking crisis and the most important developments before, during, and after the crisis, and section 3 discusses the Hall and Miles (1990) model, the EVT extension and how we can assess the probability of default using market prices. Section 4 presents the empirical results using Swedish stock market data, and section 5 concludes the paper.

2 The Swedish Banking Crisis

In the early 1990s the Swedish financial system was under severe strain due to one of the worst banking crisis that had struck an industrial nation since the 1930s. What made the banking crisis particularly critical was the simultaneous macroeconomic weaknesses and an unfolding currency crisis. The crisis led to a general recession, and between 1990 and 1993 GDP fell with a total of 6 % and total unemployment rose from 3% to 12% (Bäckström (1998)). The Swedish banks and finance companies faced an increasing amount of credit losses and six of the seven largest banks needed some kind of capital injection; either from the government or from their owners. Or as Ingves and Lind (1998) puts it "During the most critical times of the banking crisis most of the major Swedish banks faced some sort of problem, and there was a significant risk of an "implosion" regarding the number of banks in Sweden". In most respects, Sweden faced a systemic banking crisis and that was also the way it was treated by the treasury, the supervisors, as well as the central bank.

We will now briefly go through some of the events that occurred before, during, and after the crisis in a chronological way. In this way it will be easier to compare our results regarding the market's assessment of the bank default probabilities with the health of the Swedish banking sector, during the last 15 years.

1985-1989: One of the most important causes of the financial crisis was the deregulation of the Swedish credit market in November 1985 (Bäckström (1998), Lybeck (2000), Wohlin (1998))[5]. The regulated market for credit was considered part of the structural problem in Sweden at the time and by abolishing the ceiling for how much the banking system could lend, the economy was given a very strong expansive pulse. The total amount of outstanding credits doubled in the period 1985 to 1989. The fixed exchange rate system at the time (that was to be defended at any cost for political reasons) hampered the possibility for the central bank to use monetary policy to accommodate the demand chock created by the deregulation. Unfortunately, the relaxed monetary stance was not balanced by a strict fiscal policy and the result was a fast growth in the level of private debt coupled with increasing equity prices and, particularly, real estate prices. After a decade of steadily increasing stock prices the stock market peaked in 1989. It was not to turn upwards again until 1993.

1990: Fuelled by the international economic slowdown, the Iraqi invasion of Kuwait, and the German unification with its upward pressure on interest rates in Sweden, the overheated Swedish asset markets started turning downwards in 1990 leading to a flood of investors being unable to repay their (asset-backed) loans. The increased amount of non-performing loans on the balance sheets of the finance companies also concerned the market and most of their lines of credit were cut off. The government's opinion, however, was that no systemic crisis was threatening the financial system, and there was no bail out of the finance companies. Eventually, many of these finance companies collapsed under their burden of problem loans and what was coined "the finance company crisis" actually marked the beginning of the following banking crisis. Banks' returns on assets (räntabilitet) started to decline, and credit losses, that had been very moderate for most of the post-war period, started to increase in 1990. Many of the major banks had lent

[5] Bäckström is the current governor of the Swedish central bank, Wohlin is a former governor of the central bank, and prof. Lybeck is a former chief economist of the investment bank, Matteus Fondkommission AB.

extensively to the finance companies (that in turn had financed investments in real estate) and as early as 1990 Nordbanken faced significant credit losses and was in serious trouble due to the lending to some of these finance companies.

1991: One year after the finance company crisis, Sweden was in a deep recession and it was clear that many banks had severe problems. The overall returns on assets in the banking sector declined even further and most of the major banks presented negative numbers; in the case of Nordbanken the return on assets was -30% (Lybeck (2000)). The banks were facing steadily increasing amounts of non-performing debt and their credit losses as a proportion of their total outstanding debt was approaching alarmingly high levels; the overall level in the banking sector in 1991 was 5 % (Lybeck (2000)). In fall 1991 Nordbanken presented large credit loss figures and flagged for a capital injection. The government, the majority owner of Nordbanken, decided to support the bank with new capital in return for equity. Still, however, according to the Swedish authorities, their were no signs of a systemic crisis unfolding.

1992: The crisis peaked in 1992, and despite fierce defense by the Swedish central bank the fixed exchange rate had to be abandoned in late 1992 after heavy speculation against it (Fig. 1). Before that, the problems in the banking sector had been further aggravated and in spring 1992 Nordbanken needed more capital to reach the minimum 8% capital required (Ingves and Lind (1998)). This time the government bought the stakes of the remaining private owners and an extensive restructuring was initiated in the now fully state owned bank. At the same time the bank was delisted from the Stockholm Stock Exchange.

Meanwhile, in the midst of the deep recession, the financial crisis worsened, with quickly falling real estate prices leading to even larger credit losses for the banks. During late summer and early fall things grew even worse following the surprising Danish no to the Maastricht treaty and the currency crisis spreading among the European countries. In order to defend the Swedish krona the central bank raised interest rates (Fig. 2) to never before seen levels (in September the over-night rate was as high as 500% for a couple of days), further aggravating the banks' problems. The defense turned out to be pointless, and when eventually the confidence in the Swedish krona was completely lost in November 1992 nothing could stop the floating and devaluation of the krona. The depreciation (-14% against the ecu by the end of 1992 and -38% by the end of 1993) of the currency led to an even further weakening of the banks' credit stance and the overall level of credit losses in the banking sector was now 8 % of the total outstanding debt. The level of credit losses was highest in Nordbanken (over 8%), and lowest in Svenska Handelsbanken (2%) and in Skandinaviska Enskilda Banken (3%). The profitability of the major banks also fell to new lows and the overall return on assets in the banking sector was around -40%, spanning from around 0% for Handelsbanken, to -25% for Skandinaviska Enskilda Banken, and -80% for Nordbanken (Lybeck (2000)). Ultimately, six of the seven largest banks needed some kind of capital injection; either from the government or from their owners. Even though all major banks except Svenska Handelsbanken applied for government funding, in the end only Nordbanken needed government support. However, the seriousness of the situation (in the case of Skandinaviska Enskilda Banken) is well summarized by Stenberg and Örn (1996): "Skandinaviska Enskilda Banken was facing the abyss in 1992.....in the Swedish treasury a plan was even written down on how the government would rescue/bail out the bank. There was a substantial risk that the (conservative) government would have to socialize the whole banking system". And to quote Ingves and Lind (1998): "From our point of view the financial system in Sweden was on the brink of a collapse in September 24^{th}, 1992".

The Swedish government was aware of the seriousness of the situation and from September 1992 the government considered the crisis systemic. They acted accordingly and on September 24th the government presented a state guarantee protecting the creditors to all Swedish banks (Ingves and Lind (1998)). It was not until November, however, with the floating of the currency and the help of positive external impulses that some light was spotted in the dark tunnel. The Swedish economy was slowly getting on the right track again.

1993: To say that the worst was over is not the same as to say that the health of the banking system, or of the Swedish economy in general, was in order. In order to handle the problem-banks and to anchor the state bank guarantee, an independent committee for bank restructuring, "Bankstödsnämnden" was established in 1993. The stock market as a whole was recovering, however, fueled by lower domestic as well as international interest rates, a depreciation of the Swedish krona, and a general upturn in the international economy. There was also some recovering in the banking sector, with a very quick increase in the market's valuation of financial sector stocks, even though most of the major banks still showed a profitability far lower than before the crisis. Despite the general increase in asset values, however, the credit situation in most banks showed no signs of improvement. The wave of bankruptcies was still sweeping over the Swedish economy, and all the major banks did as large credit losses 1993 as 1992 (Lybeck (2000)). In late 1993 Skandinaviska Enskilda Banken manages to convince their owners to inject enough capital to cover the capital requirements (Bäckström (1998)).

1994: The situation in the banking sector as a whole was slowly getting better, and no more financial support from Bankstödsnämnden was given to the banks after 1993. Still, however, the amount of credit losses had not come down to reasonable levels and the profitability of the major banks was still lower than before the crisis. While the situation in Nordbanken and Svenska Handelsbanken had improved significantly compared to 1993, the recovery of Skandinaviska Enskilda Banken (3% credit losses and a negative returns to assets) was going slower (Lybeck (2000)). The 1993 upturn in the market's valuation of financial sector stocks was also reversed in mid 1994 in the wake of the general global interest rate increase; from early 1994 to mid 1995 the Veckans Affärers Bank&Finance Index lost 45% of its value.

1995-1996: From mid 1995 interest rates were coming down from over 9% to a more modest 4% (Fig. 2) at the same time as the krona was growing significantly stronger (Fig. 1). The banking crisis was by now more or less over and the restructured Swedish banks were coming out of the crisis strong and efficient compared to many other European banks (Lybeck (2000). Their profitability was back at pre-crisis levels and the level of credit losses was almost as low as before the crisis. The degree of state ownership in Nordbanken was progressively decreasing (in late 1996 its share was just over 50%) and in November 1995 Nordbanken was listed on the Stockholm Stock Exchange again (Nordbanken (2002)). Finally, in 1996 the state bank guarantee was replaced by the general EU bank depositors guarantee and the banking crisis was definitely over[6].

1997-2001: The Swedish banks had indisputably come strong out of the crisis. The efficiency of the restructured Swedish banking sector (Lybeck (1997)) and low interest rates are possible factors behind the steady increase in share value for the major Swedish financial institutions from 1996 up until 2000. The only periods of falling financial sector share prices are during the Asian financial crisis 1998 and when in 2000 the downturn of the whole stock market, in the wake of the IT boom/crash, dragged the financial sector down with it.

3 Assessing the Probability of Default Using Market Prices

In this section we will describe the Hall and Miles (1990) approach. The advantage of this model is that it relies solely on stock market data. We will also describe how results from extreme value theory can be combined with the Hall and Miles (1990) approach and possibly give more realistic probabilities of default.

A typical bank has both assets and liabilities and if we assume that all these claims are priced efficiently by the market then the stock price, S_t, of the bank in question could 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/liability at time t (positive if an asset, negative if a liability). I we assume that (1) holds then the expected value of the stock in the future together with the variability of the value around this expectation can tell us something about

[6] In a referendum in November 1994 Sweden decided to join the European Union (EU).

the probability of the bank actually failing (the larger the number of standard deviations the stock capital represents at time t the smaller the probability of default)

As one of the most popular models of stock price formation, the CAPM expresses the expected return of a stock, $\mathrm{E}(R_t)$ at time t as the risk free return, RF_t, at time t (for instance a Treasury bill) plus a time varying risk premium, RP_t :

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

The expectations are formed at $t-1$ and the risk premium can be thought of as the amount of risk that an investor has to be compensated for multiplied by the market price of this risk, λ_t. According to the CAPM not all risk can be expected to be compensated for, and in equilibrium only non-diversifiable risk is priced. This means that only the risk that cannot be "diversified away" should be compensated in the market by a higher return than the risk free return. If we call the amount of expected non-diversifiable risk $\mathrm{E}(\mathrm{ND}_t)$ we can change (2) to

$$\mathrm{E}(R_t) = RF_t + \lambda_t \mathrm{E}(ND_t). \tag{3}$$

Since the market participants cannot be expected to be right all the time, (3) is only true on average. The actual return between $t-1$ and t is instead given by the expected return in (3) plus a stochastic error term, ε_t, that on average is equal to zero:

$$R_t = RF_t + \lambda_t \mathrm{E}(ND_t) + \varepsilon_t. \tag{4}$$

We can now express the *expected* value of bank capital, $\mathrm{E}(S_t N)$, as

$$\mathrm{E}(S_t N) = S_{t-1} N \left\{1 + RF_t + \lambda_t \mathrm{E}(ND_t)\right\}. \tag{5}$$

and *actual* value of bank capital as depending on the random term ε_t

$$S_t N = S_{t-1} N \left\{1 + RF_t + \lambda_t \mathrm{E}(ND_t) + \varepsilon_t\right\}. \tag{6}$$

Therefore, the actual value of bank capital at time t can be divided into a deterministic part and a stochastic part,

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

and the conditional variance, as measured at $t-1$, of the value of bank capital at time t can be written as

$$(S_{t-1}N)^2\sigma^2_{\varepsilon t} \tag{8}$$

where $\sigma^2_{\varepsilon t}$ is the variance of ε_t at time t. This is the variability in the market value of the bank (or its portfolio of assets and liabilities) around the market's expected value, and this is the variability measure that is of interest to the supervisor or regulator.

If the assumption of market efficiency holds, and if we divide the value of the bank, $S_{t-1}N$, by its standard deviation $S_{t-1}N\sigma_{\varepsilon_t}$, we get a simple measure of how probable a default by time t is:

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

This metric shows the number of standard deviations that the value of the bank represents at time $t-1$ and it can easily be transformed to a default probability if we assume normality of the error term[7]. For instance, a value of $\frac{1}{\sigma_{\varepsilon_t}}$ equal to 2.33 would represent a 1 in 100 probability of default and a value of 3.09 would represent a 1 in 1000 probability of default between $t-1$ and t. As we will show below, an alternative is to fit an extreme value distribution to the (fat) tails of the errors and infer the probability of default using that distribution.

In order to get an estimate of σ_{ε_t}, the standard deviation of ε_t, we return to (2) which according to the CAPM can be rewritten as

$$\mathrm{E}(R_t) = \frac{\mathrm{E}(S_t - S_{t-1})}{S_{t-1}} = RF_t + \beta_t \mathrm{E}(RM_t - RF_t) \tag{9}$$

where RM_t is the return on the market portfolio and β_t is the expected conditional CAPM coefficient defined in its usual way as $\frac{\mathrm{E}(\sigma_{R_t,RM_t})}{\mathrm{E}(\sigma^2_{RM_t})}$. From the CAPM we also know that the risk premium on the market portfolio must be the market price of risk, λ_t, multiplied by the expected variance, $\mathrm{E}(\sigma^2_{RM_t})$, of the market portfolio returns (the expected non-diversifiable risk of the market portfolio). Thus

$$\mathrm{E}(RM_t) = RF_t + \lambda_t \mathrm{E}(\sigma^2_{RM_t}) \tag{10}$$

and, by definition, λ_t, the market price of risk, is:

$$\lambda_t = \frac{\mathrm{E}(RM_t - RF_t)}{\mathrm{E}(\sigma^2_{RM_t})}.$$

[7] We define default as the point in time when the value of the firm's capital (assets minus liabilities) is equal to zero. Of course, if some liabilities are not due at time t this measure should be modified to take this into consideration. The effect would be a reduction of the probability of default.

Rewriting (4) but for the market portfolio instead of the individual stock leaves us with

$$RM_t = RF_t + \lambda_t \mathrm{E}(\sigma^2_{RM_t}) + \upsilon_t = RF_t + \lambda_t \mathrm{E}(\sigma^2_{\upsilon_t}) + \upsilon_t \tag{11}$$

where υ_t is a random error term that on average is equal to zero just like ε_t. If we add the error term, ε_t, to (9) and substitute for the definition of β_t we also end up with an equation for the individual stock,

$$R_t = RF_t + \frac{\mathrm{E}(\sigma_{R_t,RM_t})\mathrm{E}(RM_t - RF_t)}{\mathrm{E}(\sigma^2_{RM_t})} + \varepsilon_t,$$

which, using the definition of the market price of risk finally can be written as

$$R_t = RF_t + \lambda_t E(\sigma_{R_t,RM_t}) + \varepsilon_t = RF_t + \lambda_t E(\sigma_{\varepsilon t,\upsilon_t}) + \varepsilon_t. \tag{12}$$

The coupled equations (11) and (12) contain expectations of variances and covariances and in order to model these (and to get an estimate of the distance to default measure $\frac{1}{\sigma_{\varepsilon_t}}$) we use a bivariate GARCH-M framework. Compared to earlier studies we do the estimation in a more rigorous way though. While Hall and Miles (1990) uses severely restricted non-standard versions of ARCH and GARCH, and Clare and Priestley (2002) makes a seemingly ad hoc choice of a non-standard AGARCH-M bivariate model we try to choose our model in a systematic way. First of all, 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 (particularly if one has rather short data series). Hall and Miles (1990) solves this problem by putting several restrictions on their equations and Clare and Priestley (2002) by choosing a non-standard covariance matrix representation.

In the spirit of transparency and parsimony we neglect possible asymmetries or seasonalities in the return series, and limit ourselves to a first order GARCH(1,1) representation[8]. We also choose the parsimonious constant correlation representation for the covariance matrix[9]. And finally, we assume the market price of risk, λ_t, to be constant, i.e. $\lambda_t = \lambda$, for all t. In this way we end up with a system (of excess returns) containing only 10 parameters to estimate using the method of maximum likelihood (BHHH):

[8] We have tried to estimate the system using the AGARCH-M presentation but without getting significant asymmetry parameters. The same holds for higher order GARCH(i,j) models. We find no strong seasonality patterns in the data, and dummies for weekends etc. are not expected to improve our estimates significantly.

[9] We have also successfully estimated the system using the BEKK representation. The final results did not change much and parameter estimates and final results can be requested from the author.

$$
\begin{aligned}
R_t - RF_t &= \alpha_{i,1} + \lambda E(\sigma_{\varepsilon t, \upsilon t}) + \varepsilon_t \\
RM_t - RF_t &= \alpha_{m,1} + \lambda E(\sigma^2_{\upsilon_t}) + \upsilon_t
\end{aligned}
$$

$$
\begin{aligned}
E(\sigma^2_{\varepsilon_t}) &= \phi_{i,1} + \phi_{i,2}\varepsilon^2_{t-1} + \phi_{i,3}\sigma^2_{\varepsilon_{t-1}} \\
E(\sigma^2_{\upsilon_t}) &= \phi_{m,1} + \phi_{m,2}\upsilon^2_{t-1} + \phi_{m,3}\sigma^2_{\upsilon_{t-1}} \\
E(\sigma_{\varepsilon_t, \upsilon_t}) &= \rho_{\varepsilon,\upsilon}\sqrt{E(\sigma^2_{\upsilon_t})E(\sigma^2_{\varepsilon_t})},
\end{aligned} \tag{13}
$$

where $E(\sigma^2_{\varepsilon_t})$ and $E(\sigma^2_{\upsilon_t})$ are the expected conditional variances of ε_t and υ_t (as the market perceives it), $\rho_{\varepsilon,\upsilon}$ is the correlation coefficient, $E(\sigma_{\varepsilon_t,\upsilon_t})$ is the expected covariance between ε_t and υ_t, and $\varepsilon_t = \sigma_{\varepsilon_t} u_1$, and $\upsilon_t = \sigma_{\upsilon_t} u_2$ where $u_i \sim N(0,1)$. From (13) we obtain estimates of σ_{ε_t}, the conditional variance of the individual bank's excess stock return, at each point in time that we can plug into the metric for the probability of bank default, $\frac{1}{\sigma_{\varepsilon_t}}$.

The next issue to handle is the choice of time scale. Eq. (13) gives us a constantly updated metric as to the probability of default of the bank in question within the next day, week, month or year depending on our choice of data. From a practical point of view, the most reasonable frequency for updating the default rate is probably monthly; daily estimates contain too much noise and are too frequent for most applications, and quarterly or yearly estimates are unnecessarily infrequent considering the quality of data available. To further investigate the stability of the technique, however, we have chosen to estimate such a monthly (default within a month) $\frac{1}{\sigma_{\varepsilon_t}}$ measure using both daily and monthly data (with very similar results). To create a monthly default measure from the daily σ_{ε_t} estimates we simply add up the 21 daily variances within the month (to get the monthly variance) and calculate a monthly default measure $\frac{1}{\sqrt{\sigma^2_{\varepsilon_1} + \sigma^2_{\varepsilon_2} + \ldots\ldots + \sigma^2_{\varepsilon_{21}}}}$[10].

Our next step is to calculate actual default probabilities associated with the default metric above. As mentioned earlier, in order to do so one can draw on the assumption of normally distributed error terms and simply map the metric to a probability using the negative tail of the normal distribution function. However, the tails of stock return distributions are usually fatter than those of the normal distribution and we therefore introduce a distribution well known from the field of extreme value theory; the generalized Pareto distribution (GPD). This distribution has been found to fit the fat tails of financial return distributions well; since we are mainly interested in the tails of the stock return distribution this is of relevance to us (the value of the bank is usually many standard deviations away from zero). The GPD is also based on

[10] The procedure is an approximation since it assumes independent error terms, ε_t.

sound statistics theory and compared to for instance the historical sample distribution it has the advantage of making extrapolation beyond existing observations possible.

In order to simplify estimations the idea is now to assume ε_t to be normally distributed all through the GARCH-M estimation and not until we are about to map our default metric into a probability do we explicitly acknowledge the non-normality of ε_t. This approach is similar in spirit to that of McNeil and Frey (2000) which applies the GPD to the standardized residuals resulting from a pseudo-maximum-likelihood GARCH estimation making minimal assumptions about the underlying innovation distribution[11]. Our idea is simply to model the standardized residuals $\frac{\varepsilon_t}{\sigma_{\varepsilon_t}}$ from the GARCH-M estimation (that should be close to identically independently distributed (IID)) assuming that in the center of the distribution we can expect the standardized residuals to be close to normally distributed but above a certain threshold they are better described by the GPD[12]. Remembering that the standard deviation of the standardized residuals is one, we now get the probability of default, for a certain default metric $\frac{1}{\sigma_{\varepsilon_t}}$, as the probability that a negative observation in the standardized residuals series is further away from the zero mean than the default metric (more than $\frac{1}{\sigma_{\varepsilon_t}}$ standard deviations away from the zero mean).

In order to model the standardized residuals above a threshold with the generalized Pareto distribution we apply a well known approach within the field of extreme value theory; the peaks over threshold (POT) method[13]. We start by calling an observation in our residuals series R and assume that it comes from a distribution F_R. The residuals above a certain threshold u then follow the excess distribution $\mathrm{F}_u(y)$ that is given by

$$F_u(y) = P(R - u \leq y \mid R > u) = \frac{F_R(u+y) - F_R(u)}{1 - F_R(u)}, \qquad 0 \leq y \leq R_F - u \tag{14}$$

where y is the excess over u, and R_F is the right endpoint of F_R. If the threshold, u, is high enough, Balkema and de Haan (1974) and Pickands (1975) show that for a large class of distributions F_R the excess distribution, $F_u(y)$, can be approximated by the *generalized Pareto distribution* (GPD)

$$\begin{aligned} G_{\xi,\alpha}(y) &= \left[1 - (1 + \frac{\xi}{\alpha} y)\right]^{-1/\xi} \quad , if\ \xi \neq 0 \\ G_{\xi,\alpha}(y) &= 1 - e^{-y/\alpha} \qquad\qquad , if\ \xi = 0 \end{aligned} \tag{15}$$

[11] It can be shown that the pseudo-maximum-likelihood method yields consistent and asymptotically normal estimates (Gourieroux (1997)).

[12] Caserta et al. (1998) suggests a similar combination of the historical distribution for the center of the distribution and an extreme value theory based distribution for the tails.

[13] A more detailed discussion of the POT method can be found in Embrechts et al. (1997).

for $0 \leq y \leq R_F - u$. ξ is the tail index and for the fat-tailed distributions found in finance one can expect a positive ξ. α is just a positive scaling parameter. Both ξ and α have to be determined by fitting the GPD to the actual data and we estimate the parameters with the maximum likelihood method. The choice of threshold, u, is not obvious and in this paper we refer to the Monte Carlo study in McNeil and Frey (2000) where it is shown that a choice of threshold leaving around $5 - 10\%$ of the observations above it gives good results.

When the GPD and its parameters are estimated we can write the underlying residuals distribution F_R that we are looking for as

$$F_R(u+y) = (1 - F_R(u))F_u(y) + F_R(u). \tag{16}$$

Acknowledging that $F_R(u)$ can be written as $(n - N_u)/n$ where n is the total number of returns and N_u is the number of returns above the threshold u, and that $F_u(y)$ can be replaced by $G_{\xi,\alpha}(y)$ (as well as rewriting $u + y$ as x), this expression can be simplified to

$$F_R(x) = 1 - \frac{N_u}{n}(1 + \frac{\xi}{\alpha}(x-u))^{-\frac{1}{\xi}}. \tag{17}$$

Above the threshold, u, this is the distribution we use for the residuals. Below the threshold, we assume the residuals to be normally distributed.

In the next section we present default probabilities using both the normal distribution and the GPD. However, since the procedure outlined above gives us monthly default rates while common practice is to discuss yearly default rates, we choose to scale up the monthly probabilities using the square-root rule; the yearly default probability is calculated using a yearly metric constructed from the monthly metric by dividing (scaling) the monthly metric by $\sqrt{12}$[14].

It is well known that the evaluation of default risk models is very difficult due to the few defaults occurring. In order to at least partly evaluate our technique we have chosen to compare our time varying bank default probabilities with those from the well known rating agencies Fitch and Moody's. These agencies produce ratings of financial entities around the world according to their ability to honor their obligations. Even though the different ratings do not directly imply specific failure probabilities it is relevant to note that over the long term it is possible to associate a probability of failure to each and one of the different ratings. This gives us a benchmark with which we can compare our probabilities. Compared to our monthly updated yearly failure probabilities, however, the rating institutions' yearly failure probabilities are updated only sporadically. In addition, these probabilities are taking possible government support into account and are therefore on the average lower (at least during the crisis). We will discuss this issue more in the next section.

[14] Again, this procedure is an approximation since it assumes independent monthly metrics.

4 Empirical Results

In this section the technique described in the previous section is applied to the Swedish financial sector as a whole as well as to the three major Swedish banks Nordbanken (NB), Svenska Handelsbanken (SHB), and Skandinaviska Enskilda Banken (SEB). As a proxy for the financial sector we use the Veckans Affärers Bank&Finance Index and as a market index we use the major Swedish stock index, Afärsvärldens Generalindex. As a benchmark we include a non-financial index, the Veckans Affärers Manufacturing Index, and as a proxy for the risk free interest rate we use the 3-month Stibor interest rate[15]. The return series for Nordbanken is split into two parts, January 1988 to August 1992 and November 1995 to December 2001, since the trading of the bank's stock was halted in mid 1992, when the government stepped in as the sole owner. Other than that all series cover the period January 1987 to December 2001. The rating histories for the three banks were kindly supplied by Fitch and Moody's. In the case of Fitch we use their International Long-Term ratings and in the case of Moody's we use their Bank Deposit Ratings. The default probabilities corresponding to the different ratings can be found in Fitch (2002), Moody's (2002), and in KMV (1997).

All estimations and results presented in this section are based on daily data and the constant correlation model in section 3, and some descriptive statistics are presented in Table 1[16]. The data series show rather similar as well as quite typical characteristics for stock return series with some series having very high kurtosis and high sample volatility over the time period. Only the two shorter Nordbanken series differ to any extent from the other by having less autocorrelation both in the returns and in the squared returns. The earlier Nordbanken series is also the only one with a negative mean return; not very surprising considering the systematic weakening, and eventual government bail out, of Nordbanken in this period. The squared Ljung-Box statistics indicate significant GARCH effects for all series. One can also note that, despite the banking crisis in the early 1990s, all banks (except Nordbanken) as well as the financial index have had a (positive) mean excess return over the last 15 years that is significantly higher than that of the Swedish stock market taken as a whole.

We now turn to the estimation of the bivariate GARCH-M system described by (13). To save space we only present parameter estimates (in Table 2) for the financial index modelled together with the market index. All GARCH parameters are positive and their sum is smaller than one (no IGARCH). The sample correlation with the market index ranges from approximately 0.4

[15] All data was downloaded from the EcoWin AB database.

[16] The estimations were repeated with monthly data with no major change in results. The same holds for the estimation of the BEKK model using monthly or daily data. The results can be received from the author upon request.

to 0.5 for the banks, to 0.7 for the financial index and 0.9 for the manufacturing index. The residuals are also all fairly well behaved[17].

GPD parameter estimates for the residuals $\frac{\varepsilon_t}{\sigma_{\varepsilon_t}}$ from the different bivariate GARCH-M systems fit to the GPD can be found in Table 3. The tail index is below 0.25 for all series indicating finite variance, skewness and kurtosis for all series. While the scaling parameter is significant for all series the tail index is not.

Keeping the discussion in section 2 on the development of the Swedish banking sector over the last 15 years in mind (including the development of interest rates and the Swedish currency in Fig. 1-2) we now estimate the default probabilities. In Figs. 3-7 we present our market based default probabilities, assuming either the normal distribution or the combination of the normal and the GPD described above, together with probabilities derived from Moody's and Fitch ratings (where applicable)[18]. All figures have logarithmic scales on the y-axis.

In the first two figures, Figs. 3 and 4, we can trace the "default rates" from January 1987 to December 2001 for the financial index (a proxy for the Swedish financial sector) and for the manufacturing index (a proxy for the Swedish non-financial sector). For both indices, the probability of default seems to be trending upwards over the period. The only exception being the period corresponding to the banking crisis, where the stock market assigned very different default probabilities to the financial sector and the manufacturing sector, respectively. While only a slight hike in default probability is noticeable for the non-financial manufacturing sector at the height of the crisis in late 1992, the market obviously assigned a heightened overall default rate to the financial sector as early as 1990 and as late as 1995. At the peak of the crisis the default probabilities reached 10-20 % for a couple of months. After the worst period the probability remained at around one percent for the next 12 months or so. During this period of very high default probabilities the EVT-extension does not seem to modify the normal results. For the most extreme months the reason is simply that we are below the threshold of the GPD and therefore sample from the normal distribution[19]. For the rest of the crisis months the reason is that the GPD and the normal distribution behave very similarly close to the threshold; the further out in the tail we move the larger the difference becomes. This is evident when we look at the periods before and after the crisis. In these relatively tranquil periods there are

[17] Parameter estimates for the other banks and indicies as well as parameter estimates for the BEKK representation can be recieved from the author upon request.

[18] The general results in this chapter remain unchanged when the BEKK representation is used and when the estimation is done using monthly data.

[19] For the financial index, in only 4 months, out of 180 months, do we actualy sample from the normal distribution. For the manufacturing index there are no months where we sample from the normal distribution and for the individual banks the average number of months is 4.

large differences in probabilities. While the default probabilities according to the normal model usually remain rather low the probabilities from the EVT-extended model reach probabilities close to one in a hundred; over the post-IT-crash period the risk of default according to the EVT-extended model is as high as 1% for the manufacturing index and 0.5% for the financial index.

If we compare the estimated default rates for the financial sector in Fig. 3 with the actual historical developments we can observe a close correspondence between changes in the credit environment and changes in estimated default probabilities. The finance company crisis 1990 together with the worsening situation for the banks with lower returns on assets and increasing credit losses motivated the market to assign an increasing probability of failure to the whole financial sector as early as 1990. The deep recession of 1991 and the steadily increasing amounts of non-performing debt in the banking sector further worsened the already pessimistic market perception of the future of the Swedish financial sector, but it was not until 1992, with the "default" of Nordbanken, the further increase in banks' credit losses, and the attempted defense of the currency that default probabilities reached staggering levels. The perceived risk of a total collapse of the whole financial sector reached its peak around September-November 1992 and it is also at this time that the government started considering the crisis systemic. The credit situation in most banks showed no signs of improvement in 1993 (the major banks do as large credit losses 1993 as 1992) and despite the stock market recovering in 1993, the default probabilities do not go down until early 1994. At that time the situation is finally improving (with lower credit loss levels in the bank books) and despite the gloomy stock market (from early 1994 to mid 1995 the financial index lost 45% of its value) the stock market's perception of an actual default of the sector is slowly but systematically diminishing. In 1995, the banking crisis is more or less over and the default probability is back to pre-crisis levels. The restructured Swedish banks are coming out of the crisis strong and efficient but after a further improvement in perceived credit stance in 1996 the market slowly starts to perceive an increasing possibility of default (although rising from very low levels). Some of this increased risk is probably due to the global financial crises in 1997 and 1998 and pretty much the same pattern can be observed for the manufacturing index. Actually, the non-financial sector (proxied by the manufacturing index) has faced a rapid deterioration of its perceived credit strength from 1997 onwards. The probability of default has reached particularly high levels after the collapse of the stock market in 2000, something that at least partly is due to the large weight in this index of the telecom giant Ericsson AB.

In Figs. 5-7 we study individual banks (Nordbanken, Svenska Handelsbanken, and Skandinaviska Enskilda Banken) and compare the estimated default probabilities with those assigned to the banks by Moody's and Fitch. First of all, the results for the individual banks are very similar to that of the financial index. This is not surprising considering the large weight of these three banks in the index[20]. Further, if we compare the probabilities of Moody's and Fitch on one hand with those from the model on the other hand we can see very large temporary differences. From 1995 onwards the estimated default probabilities from the normal model move around a long term level similar to that of the rating institutions for all three banks, while the probabilities given by the EVT-extended version systematically are higher with a factor five or so. More strikingly, though, are the huge differences between the market's assessment (both for the normal distribution and the GPD) and the rating institutes during the banking crisis. When the crisis is building up in 1990 there is an increase in the market based bank default probability and at least Moody's is also assigning higher default probabilities to all the banks (Fitch did not downgrade any of the banks until 1992 and in 1990 it actually upgrades Nordbanken). At the peak of the crisis in 1992 there are completely different assessments of the amount of default risk attributed to the banks by the rating agencies and the stock market. Despite multiple downgrades of the banks in 1991 and 1992 the probability of default assigned to any of these banks by Moody's or Fitch was never above 0.1%. The rating agencies consequently judged the probability of any of these banks actually defaulting to be very low. The market, on the other hand, attributed very high probabilities of default, ranging from 5 to 30%, to each of these banks.

As mentioned before, one reason for the large differences between the stock market and the rating agencies is that rating agencies incorporate the possibility of a government bail out into their default probabilities. This does not seem to have a large effect on default probabilities in tranquil periods (the long-run level is close of that of the stock market based probabilities) but during the crisis it clouds the information contained in the ratings about the actual bank health; the gradual deterioration of banks' health during 1990-1992 does not significantly affect the ratings. The changes in implied default probability are both small and delayed compared to the actual credit events occurring. If ratings are to function as carriers of information, one would also have expected some kind of rating upgrading around the announcement of the general bank guarantee in late September 1992. No such action is taken by the rating agencies, however, neither before or after the announcement.

In the second half of 1991 and the first half of 1992 the market assigned the largest probability of default to Nordbanken (over this period the market assigned an average probability that was about one-hundred times higher than the rating agencies), and ultimately, in summer 1992 Nordbanken was taken over by the Swedish government and underwent an extensive reconstruction. While the default of Nordbanken did not come as a surprise to the stock market,

[20] The market share of the five largest Swedish banks in 1995 was 86% (Lybeck (2000)).

there is no clear signal coming from the ratings that identifies Nordbanken as the weaker of the three banks. What the credit ratings correctly predicted, however, is the eventually fairly small loss to creditors.

For the two banks that survived without government help, Svenska Handelsbanken and Skandinaviska Enskilda Banken, the patterns during the crisis are quite similar. The default probabilities of these two banks remained alarmingly high (according to the market) both in 1992 and 1993 (and partly in 1994) but have since come down to levels at or below 1% and are now among the banks in Europe with highest ratings (December 2001). As expected, the deeper crisis in the case of Skandinaviska Enskilda Banken is associated with a higher default probability and the slower recovery of this bank is reflected in a longer period of elevated default probabilities.

While it is difficult to fully evaluate the accuracy of the market based default probabilities, there are at least indications pointing in the direction of these measures capturing changes in credit health faster and more fully than credit agency ratings. At the very least, it seems that credit ratings should be combined with market sentiments to create feasible default probabilities. By capturing the fat tails of stock return distributions, the EVT-extended version of the Hall and Miles (1990) model indicates much higher, as well as much less volatile, default probabilities in tranquil periods than the original model does. Whether these higher probabilities are also more realistic is hard to say.

Looking at the *relative* creditworthiness of the individual banks we can see how the stock market, Fitch, and Moody's all produce similar relative rankings of the different banks[21]. The rankings in Table 4 are based on yearly averages of the 12 monthly default probabilities each year. During the crisis, the results from Table 4 are not clear-cut but a qualitative judgement would probably be that both the stock market and the rating agencies considered Svenska Handelsbanken the most creditworthy and Nordbanken the least creditworthy of the three banks. After the crisis the market still seemed to assign a smaller risk of default to Svenska Handelsbanken than to Skandinaviska Enskilda Banken and Nordbanken that on the whole are considered similarly risky. Fitch ranked the individual banks pretty much like the market, with Svenska Handelsbanken rated higher than the other two banks that share the same rating. Before the crisis Moody's assigned identical ratings to the different banks, but starting with the crisis, Moody's started giving the banks different ratings. After the crisis Moody's also considered Svenska Handelsbanken the most creditworthy bank, followed by Nordbanken and Skandinaviska Enskilda Banken, respectively.

Even though we present our results in a different way from Hall and Miles (1990) and Clare

[21] The relative ranking is of course the same whether we assume normality or the GPD.

and Priestley (2002) we can still make some comparisons. Hall and Miles (1990) use monthly data and look at four British banks from 1975 to 1987 (up until but not including the October crash) and Clare and Priestley (2002) also uses monthly data and look at nine Norwegian banks and a financial index for different time periods between 1981 and 1995 (covering the Norwegian banking crisis). Hall and Miles (1990) finds default metrics for their banks corresponding to default probabilities of between a tenth of a thousand of a percent and short periods of one to two percent. This is rather similar to the probabilities we find for the Swedish banks, with the exception for the crisis period when the probabilities in Sweden were about ten times as high. Clare and Priestley (2002) gets similar results to us when the Norwegian financial sector is studied; the probability of a systemic default is between less than a million of a percent and thirty percent. When they look at individual banks they get a behavior of the default metrics that is very different from ours and a comparison is pointless. Their default metrics move in a much smoother way than ours, something that possibly could be caused by estimation problems due to their rather short samples of monthly data.

5 Conclusions

Using an extreme value theory extension to a model by Hall and Miles (1990) that estimates time varying default rates of banks based solely on their quoted stock market prices, we have studied the credit health of the Swedish banking sector over a 15-year period (1987-2001). This period includes the severe banking crisis that struck Sweden in the early 1990s. We find that the market's assessment of the probability of failure was significantly higher during the crisis than before or after it. This is found to hold both for the Swedish financial sector taken as a whole and for the individual banks. In accordance with what one would expect, the most troubled banks also seem to be regarded riskier by the stock market than the healthier ones, and the market's relative ranking of the different banks is, overall, the same as that of the rating agencies.

When we compare the probabilities coming from the model with those from major credit rating agencies, however, we find that the market perceived the banks as being much closer to failure than the rating agencies. The market also detected weaknesses in the Swedish financial sector much earlier (1990) than the rating agencies. Part, but not all, of this difference can be explained by the rating agencies' explicit incorporation of a possible government bail out.

Compared to the market model, that updates the probability once a month (or even daily), the rating agencies' ratings were updated, at best, on a yearly basis. Finally, our extreme value theory version of the methodology differs from the original method in periods of low default probabilities and indicates fairly high default probabilities also in the post-crisis period.

We believe our paper points out the importance of focusing not only on rating agencies when an assessment of a bank's credit health is done, but to also include the perception of the stock market. The rating agencies and the market can give fairly different indications of a bank's credit health.

Other than that, we also believe that the simple method in this paper of getting a time varying estimate of the default probability could be useful in other fields of academic research in finance and economics where default rates of firms or whole sectors are important.

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Table 1: Descriptive statistics on daily excess returns, January 1987 to December 2001.

	no. of obs.	mean (%)	std. dev. (%)	skewness	excess kurtosis	Q(12)	$Q^2(12)$
Market Index	3764	5.81	20.69	−0.06	6.04	68.12	1690.87
Financial Index	3764	8.44	32.14	0.67	18.91	97.58	1215.71
Manufacturing Index	3764	9.12	27.21	0.01	5.47	67.57	1216.00
NB, period 1	1120	−30.19	38.31	−0.10	8.42	23.87	167.61
NB, period 2	1550	22.86	35.05	0.29	2.12	13.96	108.44
SEB	3764	9.69	46.42	1.76	33.34	122.77	1904.44
SHB	3764	13.27	36.89	0.94	14.27	84.31	1651.48

Mean and std. dev. are annualized and in percent. Q(12) is the Ljung-Box statistic for the returns, $Q^2(12)$ is the Ljung-Box statistic for the squared returns and the 99 percent critical value is 26.2.

Table 2: GARCH-M parameter estimates and standardized residual statistics for the financial index modelled together with the market index.

	Market Index	Financial Index
α_1	$4.84 \cdot 10^{-4}$ ($2.47 \cdot 10^{-4}$)	$4.06 \cdot 10^{-4}$ ($2.84 \cdot 10^{-4}$)
ϕ_1	$4.12 \cdot 10^{-6}$ ($2.03 \cdot 10^{-6}$)	$4.66 \cdot 10^{-6}$ ($1.921 \cdot 10^{-6}$)
ϕ_2	0.0910 (0.00531)	0.0860 (0.00349)
ϕ_3	0.882 (0.00712)	0.903 (0.00305)
λ		1.66 (1.81)
ρ		0.678 (0.00737)
Mean	-0.0392	-0.0320
Standard Deviation	0.999	1.000
Skewness	−0.764	0.0521
Excess Kurtosis	6.76	2.62

Small numbers are standard deviations.

Table 3: GPD parameter estimates.

	Financial Index	Manufacturing Index	SHB	SEB	NB, period 1	NB, period 2
u	1.30	1.35	1.29	1.28	1.11	1.24
N_u	300	300	300	300	110	110
α	0.590	0.491	0.524	0.575	0.767	0.489
	0.0519	0.00207	0.0460	0.0507	0.115	0.0651
ξ	0.0950	0.200	0.159	0.114	0.142	0.0469
	0.0716	0.0669	0.0656	0.0756	0.134	0.0983
no. of N(0,1)	4	0	6	9	1	1

u is the threshold, Nu is the number of residuals above the threshold, and no. of N(0,1) is the number of months (out of 180 months) that the normal distribution was sampled from in order to give the default probability.

Table 4: Relative ranking of the three individual banks. The rankings are based on yearly averages of the 12 monthly default probabilities each year.

	Market			Fitch			Moody's		
	SHB	SEB	NB	SHB	SEB	NB	SHB	SEB	NB
1987	1	2		1	1	2	1	1	1
1988	2	3	1	1	1	2	1	1	1
1989	1	2	3	1	1	2	1	1	1
1990	2	1	3	1	1	2	1	1	1
1991	1	2	3	1	1	2	1	2	1
1992	1	2	3	1	2	3	2	1	2
1993	1	2		1	2	2	1	2	2
1994	2	1		1	2	2	1	2	2
1995	1	2	2	1	2	2	1	2	2
1996	1	2	3	1	2	2	1	3	2
1997	1	2	3	1	2	2	1	3	2
1998	1	3	2	1	2	2	1	3	2
1999	1	3	2	1	2	2	1	3	2
2000	1	3	2	1	2	2	1	3	2
2001	1	2	3	1	3	2	1	3	2

Rank 1 indicates the most creditworthy bank and rank 3 indicates the least creditworthy bank. If a certain rating agency gives identical ratings (default probabilities) to several banks then these banks get identical rankings in this table.

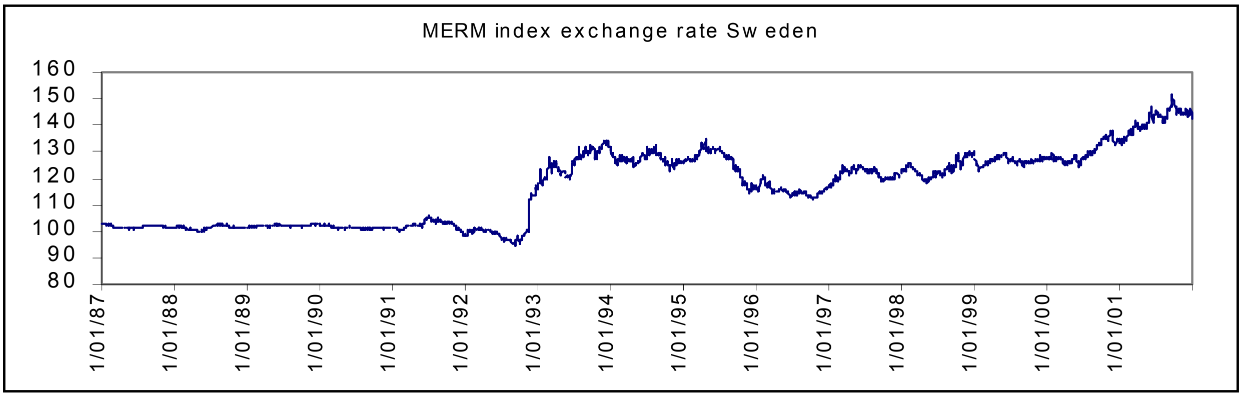

Figure 1: MERM index exchange rate, Sweden.

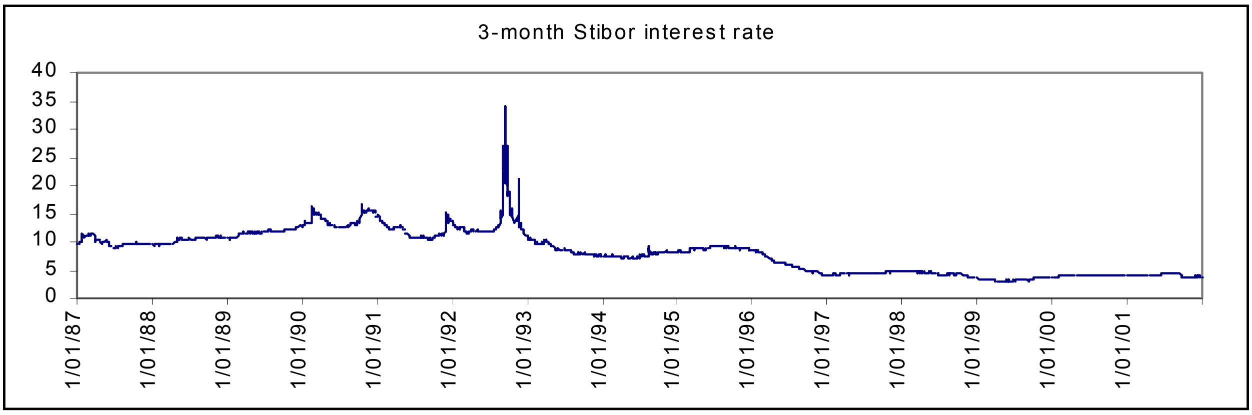

Figure 2: 3-month Stibor exchange rate, Sweden.

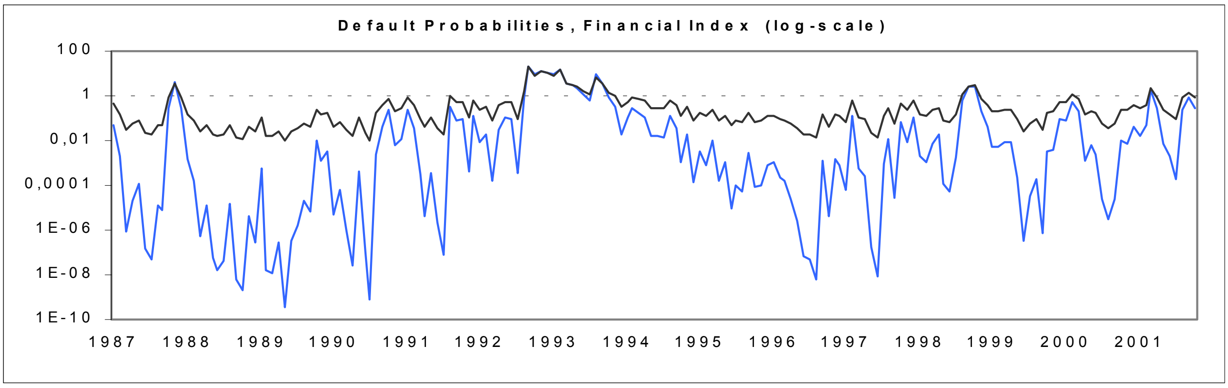

Figure 3: Default probability, financial index. The upper curve corresponds to the extreme value theory-extended model and the lower curve corresponds to the normal model. In this and the following figures 1987, 1988 and so on means January 1987, January 1988 etc.

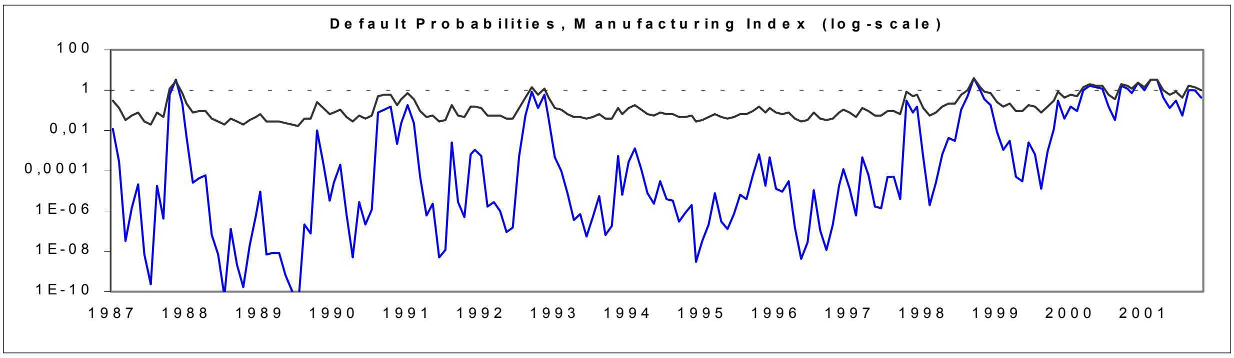

Figure 4: Default probability, manufacturing index. The upper curve corresponds to the extreme value theory-extended model and the lower curve corresponds to the normal model.

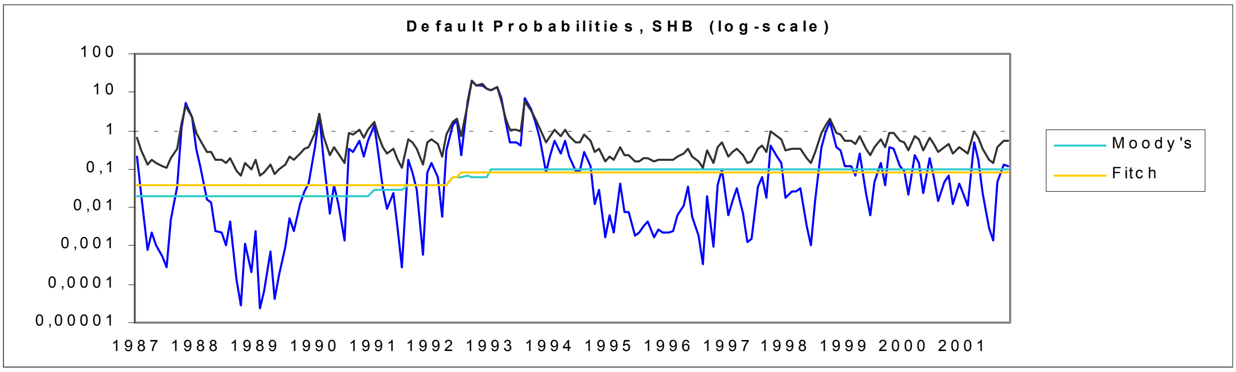

Figure 5: Default probability, Svenska Handelsbanken. The upper curve corresponds to the extreme value theory-extended model and the lower curve corresponds to the normal model. The less volatile curves correspond to the rating agencies, Fitch and Moody's, respectively.

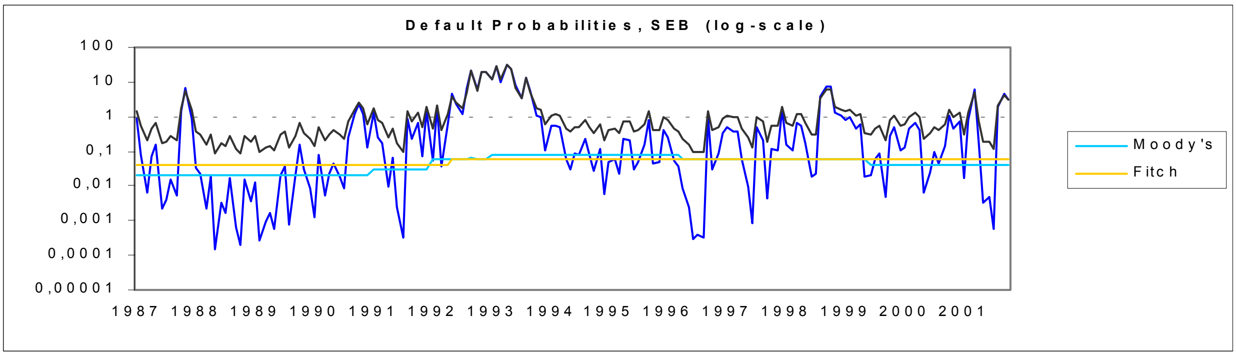

Figure 6: Default probability, Skandinaviska Enskilda Banken. The upper curve corresponds to the extreme value theory-extended model and the lower curve corresponds to the normal model. The less volatile curves correspond to the rating agencies, Fitch and Moody's, respectively.

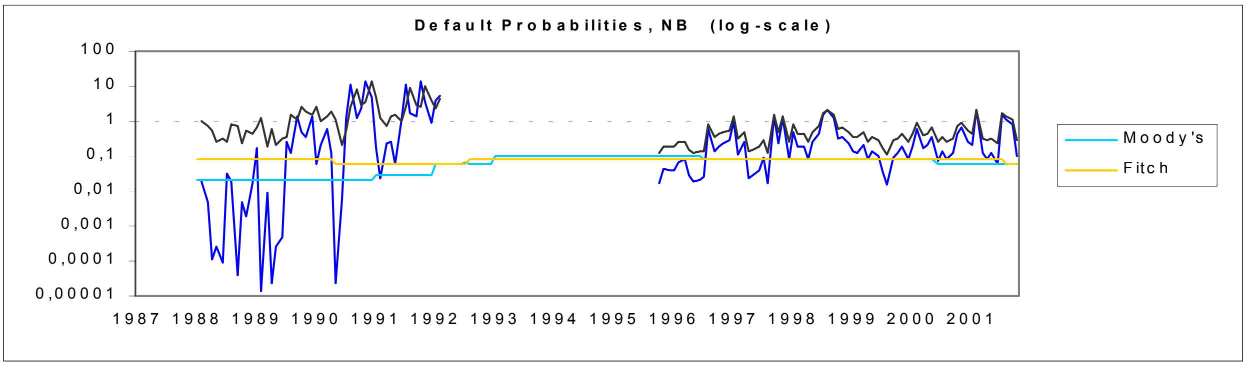

Figure 7: Default probability, Nordbanken. The upper curve corresponds to the extreme value theory-extended model and the lower curve corresponds to the normal model. The less volatile curves correspond to the rating agencies, Fitch and Moody's, respectively.