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Failure prediction of Norwegian banks: A logit approach

by

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Failure Prediction of Norwegian Banks: A Logit Approach[1]

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February 20, 2008

Abstract

Norges Bank has since 1989 been using a risk index for banks. The purpose of this risk index is to identify potential problem banks, and to obtain a general picture of the health of the banking industry. In 1994 the risk index was reconstructed based on research by Sigbjørn Atle Berg and Barbro Hexeberg. Using the Norwegian bank crisis 1988-1993 as their estimation period they concluded that it would be sufficient to include four indicators in the risk index. The risk index comprising these four indicators has been left unchanged since 1994, while the banking sector has experienced substantial structural changes. Thus, the need to re-estimate the risk index is clearly present.

In this paper a logit model is estimated based on observations from the period 2000-2005. In competition with 23 new indicators, none of the four indicators from the current risk index are included in the recommended risk index. This underlines the need to re-estimate such a risk index at regular intervals. In order to ensure that the new risk index has good properties during a deeper bank crisis than the one experienced after 2000, the predicting properties of the recommended indicators are also tested on eleven failed banks from the period 1990-93. The new risk index gives strong and early signals well in advance before the crisis culminates in all of the eleven banks. The risk index includes the following six indicators:

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(1) The capital adequacy ratio

(2) Ratio of Residential mortgages to Gross lending

(3) An expected loss measure

(4) A concentration risk measure

(5) The return on assets

(6) Norges Bank’s liquidity indicator

JEL Code: G21, G33, C25

Keywords: Norwegian banks, bank failure prediction, logit model, forecasting accuracy

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Contents

1. Introduction

Financial stability is an important prerequisite for economic growth and stability. Taking into account the substantial costs related to bank failures and systemic crisis, monitoring the probability of bank failures is of utmost importance for central banks and bank supervisory authorities, in order to prevent these events from happening. Also, the cost of crisis resolution can be reduced if pre-emptive policy action can be taken before a crisis has a chance to deepen.[2] Finally, since surveillance is both time-consuming and costly, it is important to focus the efforts on the most vulnerable and risky banks. For these reasons, Norges Bank has since 1989 been using a risk index for banks to identify potential problem banks, and to obtain a general picture of the health of the banking industry.

The risk index initially used by Norges Bank was based on the surveillance system of the Federal Reserve. It comprised seven indicators and was constructed according to the CAMEL system, except that the index did not include any indicator representing liquidity. The CAMEL system is based on the assumption that banks with low levels of *Capital adequacy, Asset quality and Management competence*, and deteriorating *Earnings and Liquidity* are more vulnerable to fail.

In 1994 the risk index was reconstructed based on research by Berg and Hexeberg (1994) on data from the Norwegian bank crisis of 1988-1993. They conducted a logit analysis on quarterly data and concluded that the following four indicators would be sufficient for the risk index:

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(1) The ratio of Gross lending to Equity capital (*Capital adequacy)*

(2) The ratio of Commercial and industrial loans to Risky assets[3] *(Asset quality)*

(3) The ratio of Interest sensitive funds[4] to Total assets *(Management Competence)*

(4) The ratio of Operating expenses[5] to Total operating income[6] *(Earnings)*

The risk index with these four indicators has been left unchanged since 1994. However, since the beginning of the 1990s, the banking sector has experienced substantial legislative changes, and technological and financial innovations.[7] Financial markets have widened and deepened, presenting banks with new opportunities and challenges for asset and liability management. The use of electronic payment systems, online banking and other automated services has been an important factor behind

[2] Thomson (1992)
[3] Total loans, bonds and certificates issued by non-government sectors
[4] Deposits from financial institutions, money market loans and borrowing from the central bank
[5] Interest and non-interest operating expenses
[6] Capital gains, interest and fee income
[7] King et al. (2006) and Villar (2006)

reduced operating expenses. Several banks have expanded into insurance and other financial services. An increased fraction of bank revenue generated from these operations has contributed to more diversified sources of income for banks and may have made them less vulnerable to negative shocks in specific sectors or markets. New financial products have also presented banks with better opportunities for hedging market and credit risk. Improved risk management systems in banks may have resulted in a more structured decision-making process with a better understanding of their risk exposures. More complex financial products, electronic payment systems, online banking and other automated services may on the other hand have increased the operational risk.

The structural changes since the early 1990s may have changed the informational contents of indicators of failure. For instance, a loan to value ratio perceived as critically high in the 1990s may be normal in today's credit market. The set of optimal leading indicators may have changed substantially. Thus, the four best indicators on bank failure during the Norwegian banking crisis 1988-93 may no longer have the optimal properties when it comes to predicting problems in today's banking sector.

Some potential indicators were excluded from the logit analysis of Berg and Hexeberg due to limitations on available data, in particular for the years prior to 1991. Specifically, indicators based on the risk weighted assets as defined by the Basel accord[8] were not available. Consequently, both better access to data and structural and technological changes suggest that the bank risk index currently at work in Norges Bank may no longer be optimal.

This paper employs a logit model in order to search for the best indicators of bank vulnerability. Section 2 gives a short description of the literature and discusses the selection of indicators to be evaluated. Section 3 provides a description of the methodology and the data employed in the econometric analysis. Section 4 details the results of the logit analysis, where the set of indicators evaluated includes both those in the current risk index and the new indicators described in section 2. The predictive powers of two recommended risk indices are tested against the current risk index within-sample in section 5, and out-of-sample in section 6. The within-sample and out-of-sample tests form the basis of the final recommendation in section 7.

2. Literature and potential leading indicators of bank failure

2.1 Literature

The early warning systems for banks originated in the United States.[9] Based on a substantial number of empirical studies appearing since the mid 1970s, the supervisors in the United States[10] adopted their

[8] See Basel Committee on Banking Supervision (1988) and (2006)
[9] Reidhill and O'Keefe (1997) give an overview of the development of such systems since the mid-1970s

first early warning systems to facilitate their off-site surveillance by providing early warnings on future bank crises.

Failure prediction models have a relatively long history in the corporate finance literature. The basic idea, originally proposed by Altman (1968), was that firms with certain financial structures have a higher probability of failure than firms with other characteristics. Altman's multivariate discriminant analysis on manufacturing firms ushered in a wave of research applying similar methodology on banks, including Stuhr and van Wicklen (1974), Sinkey (1975, 1978), Altman (1977), and Rose and Scott (1978). Nevertheless, it was Martin (1977) who set the standard for discrete-response models of bank-failure prediction. Whereas most previous research had focused on a small sample of banks over two or three years, Martin used all Federal Reserve member banks, constituting approximately 5.700 institutions. 58 banks were identified as failures during a seven-year period in the 1970s through examination of publicly available sources. Martin concluded that different indicators on Capital adequacy, Liquidity and Earnings were the most significant determinants of failure over his sample period. Other indicators on Asset quality — provision expense and loan concentration — also turned out to be significant. A host of other studies around the same time, using both logit and discriminant analysis, confirmed these basic results. Poor asset quality and low capital ratios were the two characteristics of banks most consistently associated with banking problems during the 1970s (Sinkey, 1978).

Motivated by this wave of research, the Federal Deposit Insurance Corporation (FDIC) introduced the Integrating Monitoring System in 1977. One component of this system was the humbly titled "Just A Warning System", and consisted of 12 financial ratios. The system compared each ratio observed with a benchmark value determined by examiner judgement. Banks with ratios that "failed" various screens were flagged for additional follow-up. Following a research program the Federal Reserve adopted the Minimum Bank Surveillance System, which was the first surveillance model adopted by a supervisory body to employ statistical techniques. The system examined seven financial ratios which were rated by their Z-scores and then summed to yield a composite score for each bank.

Motivated in part by the consistency of the pattern of bank solvency deterioration, the federal banking agencies adopted a rating system for banks based on the CAMEL system. Under this system "Capital adequacy" (C), "Asset quality" (A), "Management competence" (M), "Earnings" (E) and "Liquidity" (L) are each explicitly evaluated. In 1997 an indicator of "Sensitivity to market risk" (S) was adopted as a sixth component. The next year, the FDIC developed the Statistical CAMELS Offsite Rating (SCOR) model. In these systems the probability that a bank rated as "safe" will be downgraded at the next examination is estimated.

Other studies like Thompson (1992) have attempted to explain the regulator's closure decision. The methods and variables used in these studies are very similar to those behind early warnings systems.

[10] The Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC) and the Federal Reserve

The main difference is that early warning systems are constrained to use only lagged independent variables by their need to generate a timely warning for regulators.

Most European early warning systems were developed in the early 1990s as a consequence of the banking crisis in Scandinavia and the more covert crises in other European countries. The European systems were to a large extent based on the US experiences. The structural changes since the early 1990s have also motivated some research in the recent years. Logan (2003) employed a logit model to analyse distinct characteristics of banks in Britain that failed compared with those that survived in the early 1990s. Logan concluded that indicators like leverage, (low) loan growth, profit, net interest income and liquidity were good short-term predictors of failure. The best longer-term leading indicator of failure was rapid loan growth at the peak of the previous boom.

Kuznetsov (2003) employed an approach similar to Logan's for the analysis of bank failure determinants during the Russian banking crisis of 1998. Kuznetsov concluded that medium-sized banks with large investment in government bonds were more likely to survive the crisis, whereas differences in the profitability and liquidity of banks appeared to have no influence on the probability of failure. In contrast, Golovan et al. (2003) found that the probability to fail was negatively related to capital adequacy, liquidity and the share of investments in government bonds. This is in line with the conclusion from the logit analysis by Lanine and Vennet (2005) who also studied the Russian banking crisis of 1998.

In Austria, both Hayden and Bauer (2004) and Halling and Hayden (2006) have analysed the explanatory factors behind problems experienced by around 150 Austrian banks during the period 1995-2002. As there have hardly been any cases of actual bank default in Austria during this period, Hayden and Bauer (2004) defined default as a situation where a bank was facing such serious trouble that it seemed unlikely to survive without some kind of intervention. The preferred model of Hayden and Bauer included four indicators representing profitability, four indicators covering aspects of credit risk, two indicators measuring capital structure and one assessing other bank characteristics. The classification accuracy of the model was satisfactory and very stable over various data samples.

Halling and Hayden (2006) used the same sample and definition of default as Hayden and Bauer (2004). They proposed a two-step approach where a multi-period logit model was first employed to determine whether a bank is at risk. The sample of banks predicted to be at risk was then used to estimate a discrete survival time model using bank-specific variables observed at the time when banks come at-risk according to the first step in the analysis. The two-step approach outperforms the one step model of Hayden and Bauer (2004) in terms of in-sample and out-of-sample accuracy. They find that the performance advantage of the two-step model can be attributed to the two-step procedure itself, where a separate model is estimated for at-risk banks, rather than to the better definition of survival time. The two-step model includes an indicator measuring market share as bank size relative to total bank size in the home region, and also the ratio of net interest income to the number of employees as an indicator of management quality. The fact that these two indicators turns out to be highly

significant for the sample of at-risk banks might potentially reveal that the size relative to competing banks and the management quality are especially important in situations of financial crisis.
Finally, Derviz and Podiera (2004) employed an ordered response logit model to analyse the migration of S&P ratings of the three largest banks in the Czech Republic during the period 1998-2001. They concluded that predictors representing capital adequacy, credit spread[11], and total loans to total assets had significant explanatory powers.

2.2 Potential leading indicators of bank failure

The candidate indicators for this study are selected on the basis of results from previous empirical studies and prior beliefs based on theory and experiences from surveillance and analysis undertaken in Norges Bank. As the risk index is intended to warn with sufficient lead time about a potential crisis in the future, it is important to look for forward-looking indicators. If the time interval between the first warning and the date of crisis is too short, it may be too late to take preventive action at the problem banks. Moreover, the risk index should provide added value to the information which Norges Bank already has access to from other channels. The potential indicators should also be robust in the sense that they have a good predictive ability across different kinds of bank crises. Indicators which are only able to predict mild set-backs or only crises with very distinctive features should be avoided. For instance, several banks experienced substantial loan losses during the period 2002-2004 due to a crisis in the fish farming industry. Thus, indicators measuring the share of loans to the fish farming industry would probably have been able to predict this crisis fairly well. However, the industries causing the highest loan losses are unlikely to remain the same across time. Thus, it is important to search for common features of different bank crises.

To ensure coverage of the most important aspects of bank vulnerability we organize our discussion of potential indicators according to the well established CAMEL system. Several indicators representing *Capital adequacy* were found relevant by for instance Sinkey (1975) and Martin (1977), and more recently by Golovan et al. (2003), Derviz and Podiera (2004), Hayden and Bauer (2004), and Lanine and Vennet (2005). Capital serves as a buffer for unexpected losses. Thus, the higher the capital ratio, the less likely it is that losses will make the bank fail. Indicators of capital adequacy based on the risk weighted assets as defined by the Basel accord can be computed from September 1991. The advantage of these indicators is that the risk inherent in the bank's assets to some extent is taken into account when the capital adequacy is considered. If differences in the riskiness of different assets are not taken into account, the capital adequacy of banks with more risky assets will be underestimated and vice versa.

[11] Three month PRIBOR minus nominal interest rate on deposits

Indicators representing *Asset quality* were also found relevant in several studies, see for instance Martin (1977), Avery and Hanweck (1984), Gajewski (1988), Gonzalez-Hermosillo (1999), Hayden and Bauer (2004) and Halling and Hayden (2006). King et al. (2006) argue that the share of property related lending can measure how vulnerable banks are to a housing crisis. More generally, many banking crises have shown that the loan portfolio composition is a crucial determinant of the bank risk profile. Risk concentration is one important source of concern.[12] Some studies argue that the size of the bank can reflect the ability to diversify risk.[13] A second indicator assessing the risk concentration more directly can be calculated as a Herfindahl-index, i.e. by adding up the squares of the share of loans to different sectors and industries in the loan portfolio.[14] While an indicator value close to 1 indicates high concentration risk, a value close to 0 indicates diversification. A third indicator is the ratio of risk-weighted assets to different balance sheet figures, which may measure the proportion of very risky assets held by the bank. Finally, Bell and Pain (2000), Jiménez and Saurina (2006) and several other studies[15] argue that the lending growth of banks is a leading indicator of future banking problems. This is especially the case for banks that pursue high lending growth in unfamiliar markets. The bank then risks adverse selection in the sense that its pool of prospective new borrowers is composed disproportionately of those rejected by other banks.[16] According to empirical studies it takes approximately four years before the increased credit risk associated with high credit growth culminates in substantial loan losses and banking crises. The lending growth will normally fall just before the crisis. This could be explained in several ways. The weakened banks may have to write off past loans, their funding situation may become more difficult, the capital adequacy requirement may become effective, or they may have to reallocate their staff resources away from sales and marketing towards nursing existing customers.[17] In order to take the different aspects of lending growth into account, indicators should be constructed and tested on different time leads on the crisis.

Management competence is very difficult to measure based on data from the balance sheets or the income statements. Halling and Hayden (2006) concluded that the size relative to competing banks may reflect the quality of the management.[18] The access to competent labour is normally more limited in the small towns where several of the minor banks tend to be located. Competence is more easily attracted to the larger units for economic analysis and research offered by the largest banks. Indicators assessing the risk concentration may also reflect the management's ability to diversify risk. Finally, the average salary per employee is another potential indicator of the bank's competence.

[12] Lis, Pagés and Saurina (2000) og Jiménez and Saurina (2005)
[13] Arena (2005), Lis et al. (2000) and Logan (2001)
[14] Thomson (1992)
[15] Berg and Hexeberg (1994), Jiménez and Saurina (2005), Lis et al. (2000) and Logan (2003)
[16] Broecker (1990)
[17] Logan (2001)
[18] Kolari, Glennon, Shin and Gaputo (2002), Logan (2001) and Thomson (1992)

Mar-Molinero and Serrano-Cinca (2001) analysed a data set of 66 Spanish banks based on multidimensional scaling (MDS) techniques. They concluded that deteriorating *Earnings* was the most important factor in explaining why 29 of the banks failed. Several studies recommend that indicators of return on capital be included as potential indicators for *Earnings* in the CAMEL system.[19] Indicators of return on capital capture both the income that a bank earns and the efficiency of bank operations (personnel and other costs). Several studies argue that indicators measuring loan losses or provisions as a share of gross lending[20] are leading indicators of bank crisis, because deteriorating profit is often caused by substantial loan losses. Indicators representing loss provisions will be more forward-looking than indicators measuring loan losses as banks will normally increase their provisioning when they expect losses to accelerate.

In the Norwegian context it is also possible to construct an indicator measuring expected losses based on the composition of the loan portfolio with estimated SEBRA[21] coefficients for the probability of company bankruptcies and based on historical losses for personal loans. As the interest margin affects the net interest income that a bank earns from its lending activities, the interest margin is another potential candidate for the risk index.[22] Finally, as many banks have expanded into new activities, it seems relevant to test indicators measuring the fraction of fee income generated from investment banking, insurance and other financial services. A higher fraction of income from these activities may indicate a better diversification of bank income.[23]

Indicators assessing *Liquidity* capture the ability of a bank to meet deposit outflows and credit line withdrawals by selling assets or by acquiring additional liabilities. Indicators of *Liquidity* were rarely found relevant in the early U.S. studies. This is consistent with the assumption that liquidity problems are symptoms of a crisis rather than the cause of it. However, the structural changes experienced during the last decades have probably made bank funding structures and banks' ability to raise new funding more critical. Golovan et. al. (2003) concluded that the probability to fail was negatively related to liquidity. When it comes to potential indicators of *Liquidity* in the Norwegian context, the liquidity indicator[24] published semi-annually by Norges Bank in the Financial Stability Report is an obvious candidate. Total deposits as a share of gross lending will also be a potential candidate for the

[19] Arena (2005), Hanweck (1977), Logan (2001), Jagiata et. al. (2003), Lanine and Vennet (2005), Martin (1977), Pantalone and Platt (1987) and Thomson (1992)
[20] Arena (2005), Jagiata et al. (2003), Kolari et al. (2002), Martin (1977), Pérez et al. (2006) and Oshinsky and Olin (2006)
[21] The SEBRA model predicts the probability of default based on 12 explanatory variables attached to figures from the annual accounts of listed enterprises in Norway and some other characteristics. See Bernhardsen (2001)
[22] Arena (2005), Demirgüç-Kunt and Detragiache (2000) and Lis et al. (2000)
[23] King et al. (2006) and Logan (2001)
[24] The liquidity indicator is defined as the ratio of stable sources of funding to illiquid assets. An increase in the ratio indicates lower risk of liquidity problems. Deposits from households, non-financial enterprises and municipalities, bonds, subordinated loan capital and equity are considered to be stable financing. Banks' drawing facilities are not taken into account. Illiquid assets include: gross lending to households, non-financial enterprises and municipalities, other claims, assets acquired by recovery claims, and fixed assets.

risk index as deposits are one of the most stable and least costly sources of funding.[25] A falling fraction of deposits on the balance sheet may reflect funding problems, because banks normally want this fraction to be as high as possible. Increased dependence on funding in the interbank market can also increase the risk of contagion from other banks experiencing liquidity problems. Finally, Derviz and Podiera (2004) argue that banks with liquidity problems tend to raise their deposit rates in order to attract liquidity. Thus, banks facing liquidity problems are expected to have higher deposit rates.

Beaver (1968) and later Clark and Weinstein (1983) used movements of share prices as an indicator of firm bankruptcy probabilities and found that the stock market anticipates bankruptcy at least a year before it happens. A couple of decades later, Clare and Priestley (2002) calculated the probability of failure of the Norwegian banking sector both before and after the Norwegian banking crisis. In the analysis they employed a market-based measure of risk representing the variability of the bank's assets and liabilities. Clare and Priestley found evidence of a steep increase in the risk exposure of the Norwegian banking sector as a whole and in individual problem banks from 1984, following the deregulation in of the Norwegian banking sector. They also found that risk levels in the banking sector fell after 1992 and continued to fall to pre-1982 levels by the end of 1995.

As accounting data is backward-looking and only available with a considerable time lag, Blåvarg and Persson (2003), Clare and Priestley (2002) and Gropp et al. (2002) recommend using capital market information when analysing the fragility of the banking sector. As opposed to accounting information, market indicators reflect investor confidence. During the recent subprime crisis, even small loan losses or the announcement of negative news triggered large movements in the markets, increasing funding costs and hurting bank earnings. Thus, the role of liquidity risk and confidence in banks seem to be far more important than during the Norwegian banking crisis of 1988-1993. However, the use of capital market indicators has also some drawbacks. Market liquidity effects, herd behaviour and several other mechanisms in the capital market may produce substantial variation in market indicators that is not related to the bank's probability of failure. Thus, market indicators may give misleading signals regarding the banks' fragility. Moreover, data on equity and bond markets is only available for a minor portion of the banks included in the risk index of Norges Bank. Equity prices, interest-spreads, distance-to-default and other market indicators should still be monitored in addition to the risk index when the quality of the data is acceptable.

Finally, some studies are employing macroeconomic indicators, because bank distress is assumed to be related to business cycle conditions.[26] Macroeconomic indicators can only be employed in order to analyse the risk inherent in the Norwegian banking sector as a whole. However, Gonzalez-Hermosillo

[25] Demirgüç-Kunt and Detragiache (2000) og Jagiata et. al. (2003)
[26] Davis and Karim (2007), Demirgüç-Kunt and Detragiache (2000), Gonzalez-Hermosillo (1999), Jordan and Rosengren (2002), and Kamisky and Reinhard (1996)

et al. (1996) document that while bank-specific variables are better in explaining the probability of bank crises; macroeconomic variables seem to be important for the timing of failure. Thus, macroeconomic indicators should be employed as a supplement to accounting information and market indicators in the analysis of Norwegian banks.

3. Sample and methodology

3.1 Methodology

The aim of this study is to identify the set of indicators that best discriminates between problem and non-problem banks in the Norwegian banking sector. Model generated probabilities of failure can be used as early warnings and as signals that banks with high and increasing failure probabilities should be analysed in more detail and, if necessary, that pre-emptive or remedial policy action should be taken.

Logit analysis will be employed in the study. After Martin introduced a logit model for banking failures in 1977, a wave of research has applied the same methodology. Logit models are employed to find the explanatory factors behind a certain event taking place, in this case a bank failure. The dependent variable is constructed as a binary variable, i.e. a dummy-variable. It takes the value 1 if the bank has failed within a defined time period and the value 0 if the bank did not fail. The modelled probabilities constitute a non-linear S-shaped function within the interval (0, 1). Consequently, the effect of changes in the explanatory variables on the crisis probability depends on its initial level. A given change in an explanatory variable will make little difference to the probability of failure if the probability is initially very low (or very high). However, if the initial probability is in the 0.5 range the same change in the explanatory variable will trigger a much stronger effect on the probability of failure. This seems intuitively plausible since sound banks with high asset quality, liquidity, earnings and management competence are less vulnerable to negative shocks (i.e. marginal changes in the independent variables) than banks performing less well. Also, if a bank has an extremely high probability of failure (close to 1), it is reasonable that a change in one of the independent variables will have little effects on its prospects.

3.2 Definition of bank failure

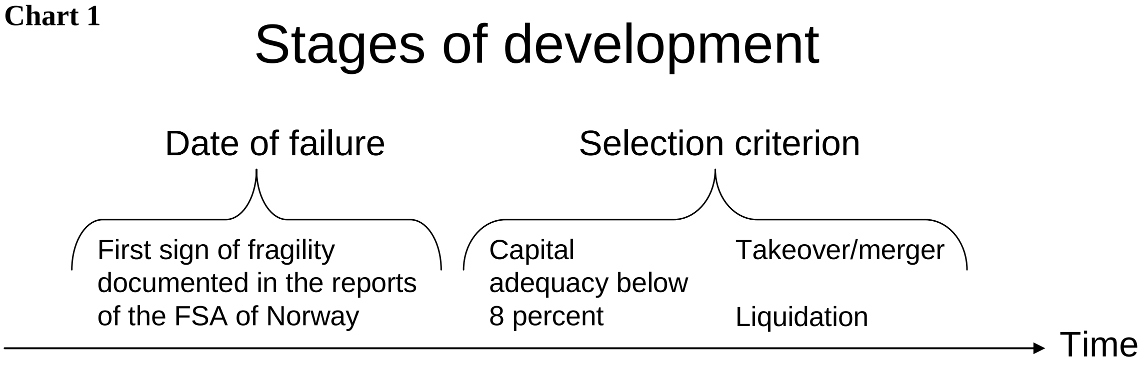
Enterprises are normally defined as bankrupt when the net worth becomes negative. However, most bank problems are resolved in some way before the net worth becomes negative. In Berg and Hexeberg’s study banks were considered problem banks at the time when they applied for assistance from an insurance fund. However, the banks experiencing problems in the period 2001-2005 did not seek assistance from the insurance fund, nor did they receive liquidity support from Norges Bank.

Thus, a broader definition of bank failure is called for. In the present study a bank is defined as having failed if it underwent any one of the following three events due to illiquidity or insolvency*:*

1. *Liquidation*
2. *Take over or merger*
3. *Capital adequacy ratio below 8 per cent*

These three criteria for defining bank failure will normally be met at different stages of the crisis. A bank normally, but not always, violates the capital requirement before it is taken over, merged or liquidated. Therefore, the broad definition of bank failure makes it rather challenging to date failures in a comparable fashion for banks failing according to different criteria. A less ambiguous definition might have been preferable. The number of failed banks in the sample would, however, be reduced substantially if the definition was based on only one or two of the above criteria.
In the present study, *the date of failure of the problem banks*, as selected given the above definition of bank failure, *is set equal to the date when the first sign of insolvency and/or illiquidity is documented in the internal reports of the Financial Supervisory Authority of Norway*. This ensures that failure is dated in the same way for all banks, and at a stage when the crisis banks have not yet shown very clear signs of insolvency and/or illiquidity.

Chart 1



3.3 Sample

The time span of failures covered by the present sample is 2000Q3-2005Q2, when a number of banks did fail according to our definition. The sample of banks does not include branches of foreign banks, because transactions and funding from the parent bank often produce extreme values of the indicators. Also, the supervisory authorities have limited responsibility regarding supervision of these branches.[27] Eight new banks were established during the sample period.[28] These banks are not included in our sample as banks will normally have extreme indicator values during the start-up process. One of the

[27] Borchgrevink and Moe (2004)
[28] Romsdals Fellesbank (2000), Jernbanepersonalets Sparebank (2001), Acta Bank (2001), Bankia Bank (2001), Storebrand Bank (2001), Landkreditt Bank (2002), Sparebanken Telespar (2003) and Verdibanken (2003)

problem indicators requires data back to 1996 Q3. Thus, Privatbanken is also excluded from the sample, because it was established in late 2000. The number of banks in our sample was also reduced by mergers between sound banks during the estimation period.[29] Applying backward aggregation prior to these mergers reduces the initial sample by five banks. The failed banks are also excluded from our sample at the date of failure. Altogether, the sample consists of 136 banks as of September 2000, and 128 banks by the end of the sample period in June 2005. Table 1 lists the eight failed banks in the sample:

Table 1

Bank	**First signal to the FSA of Norway**	**Event 1 in the definition of failure**	**Event 2 in the definition of failure**	**Gross lending 2000Q3 (MNOK)**
Nordlandsbanken	2002Q1	Capital adequacy below 8 percent (2002Q4)	Taken over by DnB NOR (2003Q1)	18145
Finansbanken		Merged with Storebrand Bank (2003Q1)		12857
Helgeland Sparebank	2002Q2	Merged with Rana Sparebank (2005Q2)		4364
Kredittbanken		Taken over by Islandbanki (2004Q4)		2925
Nesset Sparebank	2002Q3	Capital adequacy below 8 percent (2003Q2)		535
Sparebanken Flora-Bremanger	2002Q4	Capital adequacy below 8 percent (2003Q2)	Merged with Sparebanken Sogn og Fjordane (2003Q3)	1771
Enebakk Sparebank		Taken over by Lillestrøm Sparebank (2003Q1)		95
Sparebanken Rana	2003Q1	Merged with Helgeland Sparebank (2005Q2)		4314

For evaluating systemic risk, it is particularly important that the risk index identifies problems arising at the largest banks. As reported in the right column of table 1, Nordlandsbanken was the largest failed bank in our sample. In terms of gross lending, the size of the second largest failed bank, Finansbanken, amounted to 70.9 per cent of the size of Nordlandsbanken as of 2000Q3. The gross lending of Helgeland Sparebank and Sparebanken Rana amounted to 24.1 and 23.8 per cent, respectively, of the gross lending of Nordlandsbanken. The remaining four failed banks in our sample were far smaller.

Our sample includes a total of 2622 observations. That leaves us in the clear relative to the objections raised by Stone and Rasp (1991), who concluded that logit models with 4-6 independent variables estimated on less than 200 observations showed signs of skewed t-statistics and coefficients. However, due to the absence of any deep banking crisis during the sample period, the number of failed banks in our sample is smaller than desired.[30] As for the number of failures, the sample of Berg and Hexeberg (1994), comprising 25 failed banks, was far better.

[29] Øksendal Sparebank merged with Tingvoll Sparebank (2001), Bergensbanken with Svenske Handelsbanken AB (2001), Stangvik Sparebank with Surnadal Sparebank (2001), DnB Bank with Gjensidige NOR Sparebank (2004), and Lunde Sparebank merged with Holla Sparebank (2004).

[30] Hamilton (1992)

3.4 Data

The data used to investigate potential leading indicators were drawn from the Bank Statistics of Norges Bank, Statistics of Norway and the Financial Supervisory Authority of Norway. The explanatory powers of the following indicators are evaluated (abbreviations used for the indicators in the following analysis are listed in parentheses):

Table 2

Capital adequacy

(1) Ratio of Gross lending to Equity capital (L/E)

(2) Ratio of Core capital to risk weighted assets (CCAP)

(3) Ratio of Core and supplementary capital to risk weighted assets (CAP)

Asset quality

(4) Ratio of Commercial and industrial loans to Risky assets (CIL/RA)

(5) Ratio of Risk weighted assets to Total assets (RWA/TA)

(6) Changes in indicator (5) measured in percentage points (rwa/ta)

(7) 12-month growth in Gross lending measured in per cent (LG)

(8) Squared deviation from the mean sample value of indicator (7) (LG2)

(9) Ratio of Residential mortgages to Gross lending (MOR/L)

(10) Expected loan losses in per cent of gross lending, based on estimated bankruptcy probabilities for each category of borrowers in loan portfolio (ELOSS)

Management competence

(11) The Herfindahl concentration index of sectors in the loan portfolio (CONS)

(12) Ratio of Interest sensitive funds[31] to Total assets (ISF/TA)

(13) Market share measured as share of Total assets (SIZE)

Earnings

(14) Ratio of Operating costs to Total operating income (C/I)

(15) Ratio of Commission income to Total assets (CI/TA)

(16) Ratio of Annualised profit before taxes earned over the past three months to Equity capital (ROE1)

(17) Ratio of Profit before taxes earned over the past 12 months to Equity capital (ROE2)

(18) Ratio of Annualised profit before taxes earned over the past three months to Total assets (ROA1)

(19) Ratio of Profit before taxes earned over the past 12 months to Total asset (ROA2)

(20) Total interest margin[32] measured in per cent (INTMARG)

(21) Ratio of Total provisions over the past three months to Gross lending (PROV)

[31] Deposits from financial institutions, money market loans and borrowing from the central bank
[32] Lending margin plus deposit margin.

(22) Ratio of Specific provisions over the past three months to Gross lending (SPROV)

(23) Ratio of Loan losses over the past three months to Gross lending (LOSS)

Liquidity

(24) Norges Bank's liquidity indicator[33] (LIQ)

(25) Ratio of Deposits to Gross lending (DEP/L)

(26) Changes in indicator (24) measured in percentage points (dep/l)

(27) Deposit rate[34] less the average deposit rate of the banks in the sample (DEPRATE)

Indicator (8) is calculated based on the bank's loan growth and the (unweighted) average loan growth of all banks in the sample period. The deviation from the average loan growth of 13.02 percent (see LG in table 3 below) is then squared in order to identify both banks with very low or negative loan growth and banks with very high loan growth.

Indicator (10) is based on the composition of the loan portfolio, together with an estimated model for the probability of company bankruptcies and historical frequencies of losses on personal loans. The expected losses for commercial and industrial loans are calculated by multiplying the gross lending to each sector with the corresponding probability of bankruptcies. The expected losses for personal loans are calculated by multiplying the personal loans with the average historical losses (in percent) for personal loans in Norway during the 1990s. The corporate loan portfolio is composed of nine different sectors;

- Primary industries,
- Property management,
- Commercial services,
- Mining,
- Oil and gas,
- Shipping abroad,
- Other transport,
- Construction and
- Retail trade, hotel and restaurant.

Indicator (11) is calculated as a Herfindahl index, i.e. by adding up the squares of the share of loans to each of the nine corporate sectors and personal loans. While an indicator value close to 1 indicates high concentration risk, a value close to 0 indicates diversification. Indicator (13) is calculated by dividing the bank's total assets on the total assets of all the banks in the sample.

[33] See footnote 24.
[34] Annualised interests on deposits over the past three months to deposits.

Finally, indicator (27) is the difference between the bank's deposit rate and the average deposit rate of the sample during the same quarter. A positive deviation from the average deposit rate may signal that liquidity problems have forced the bank to raise its deposit rate.

In table 3 below (unweighted) means and standard deviations of each of the potential indicators are reported:

Table 3

Variable	Means	Standard deviations	Variable	Means	Standard deviations
Failure	0.003	0.06	C/I	0.79	0.09
L/E	9.33	2.93	CI/TA	0.55	0.17
CCAP	15.78	5.48	ROE1	0.11	0.10
CAP	16.40	4.91	ROE2	0.12	0.07
CIL/RA	0.26	0.11	ROA1	0.011	0.009
RWA/TA	65.33	6.93	ROA2	0.013	0.007
rwa/ta	-0.830	3.16	INTMARG	2.80	0.76
LG	13.02	12.12	PROV	1.64	0.85
LG2	146.93	2524.9	SPROV	0.17	0.48
MOR/L	71.36	15.61	LOSS	0.29	0.36
ELOSS	0.002	0.0006	LIQ	98.57	15.12
CONS	0.55	0.14	DEP/L	80.55	16.57
ISF/TA	0.23	0.17	dep/l	2.40	5.90
SIZE	0.76	4.01	DEPRATE	0	0.80

4. Estimation and analysis

4.1 Correlation analysis

High correlation between independent variables can potentially introduce multicollinearity which, in turn, may lead to a downward bias in the t-values of estimated coefficients. All indicators representing *Capital adequacy* are highly correlated, confer table 4 below. The correlation coefficient between CCAP and CAP is 0.96, whereas CCAP and L/E are strongly negatively correlated in our sample. The correlation pattern implies that only one of these three indicators should be included in a well specified model.

Table 4

	L/E	CCAP	CAP
L/E	1.000		
CCAP	-0.857	1.000	
CAP	-0.761	0.961	1.000

Some of the indicators assessing *Asset quality* (table 5) correlate strongly. The share of commercial loans (CIL/RA) correlates positively with the expected loss indicator ELOSS and negatively with the mortgage lending indicator MOR/L. The two indicators covering lending growth (LG and LG2) are also correlated, making it problematic to include both these indicators in the model.

Table 5

	CIL/RA	RWA/TA	rwa/ta	LG	LG2	MOR/L	ELOSS
CIL/RA	1.000						
RWA/TA	0.558	1.000					
rwa/ta	-0.018	0.146	1.000				
LG	0.049	0.075	0.198	1.000			
LG2	0.015	0.000	0.075	0.722	1.000		
MOR/L	-0.681	-0.415	-0.050	-0.123	-0.222	1.000	
ELOSS	0.891	0.446	0.005	0.015	0.088	-0.621	1.000

In contrast, the correlation between the indicators representing *Management competence* is low (table 6). SIZE (the bank's market share) correlates negatively with CONS. This is in line with our expectations that the loan portfolio of smaller banks tends to be less diversified.

Table 6

	CONS	ISF/TA	SIZE
CONS	1.000		
ISF/TA	-0.119	1.000	
SIZE	-0.271	0.001	1.000

Some of the indicators representing *Earnings* (table 7) also correlate strongly. While the correlation between quarterly profit ratios to equity and total assets, ROE1 and ROA1 respectively, is 0.89, the correlation between annual profit ratios, ROE2 and ROA2, is 0.77. These high correlation coefficients suggest that the recommended risk index should only include one indicator based on quarterly annualised profit and only one indicator based on the profit earned over the past 12 months.

Table 7

	C/I	CI/TA	ROE1	ROE2	ROA1	ROA2	INTMARG	PROV	SPROV	LOSS
C/I	1.000									
CI/TA	-0.028	1.000								
ROE1	-0.408	0.061	1.000							
ROE2	-0.419	0.100	0.562	1.000						
ROA1	-0.528	-0.003	0.886	0.441	1.000					
ROA2	-0.566	-0.008	0.412	0.774	0.555	1.000				
INTMARG	-0.093	0.156	0.054	0.065	0.099	0.144	1.000			
PROV	0.089	0.005	0.152	0.196	0.036	0.018	-0.163	1.000		
SPROV	-0.046	0.005	0.122	0.131	0.099	0.079	0.041	0.330	1.000	
LOSS	0.081	-0.030	-0.443	-0.317	-0.470	-0.345	0.075	0.288	0.144	1.000

Finally, the correlation matrix of the indicators assessing *Liquidity* (table 8) indicates that it may be problematic to include both LIQ and DEP/L in the model. The explanation behind the high correlation coefficient (0.73) is probably that deposits is classified as a stable source of funding in the liquidity indicator of Norges Bank (LIQ).

Table 8

	LIQ	DEP/L	dep/l	DEPRATE
LIQ	1.000			
DEP/L	0.731	1.000		
dep/l	-0.133	-0.170	1.000	
DEPRATE	-0.032	-0.116	-0.058	1.000

4.2 Estimation and analysis

As discussed in section 3.2, a model developed for predicting future bank failures has to use indicator values observed with a sufficient lead time to the first sign of bank illiquidity or insolvency. In line with the logit analysis of Berg and Hexeberg (1994), we observe indicator values one, two, three and four quarters prior to the date of failure. Notice, however, that we date the event of failure at an earlier stage (the point in time when the first sign of insolvency and/or illiquidity is documented in the reports of the FSA) than in Berg and Hexeberg's analysis (the point in time when banks applied for assistance from an insurance fund). As a short lead time produces more significant results, the following analysis will initially focus on models with a lead time of one quarter, i.e. indicator values are observed at the end of the quarter before failure. However, results from models with a lead time of two, three and four quarters are also reported, and are shown to be consistent with the models with shorter leads. All variables, except loan growth, are observed at the exact lead time, on the assumption that historical values do not contain additional information. The 12 month loan growth (LG) is included for each of the past three years, in order to take loan growth over a longer time span into account.

We initially apply an estimation procedure where all the 27 indicators proposed in section 3.4 are included. The required level of statistical significance is set at 10 %. By excluding sequentially the least significant variables, we end up with a model that includes only statistically significant indicators. As a cross check we employ a nested-models strategy similar to F-tests in ordinary least squares (OLS) estimations. Finally, variables with counterintuitive signs on the estimated coefficients are excluded. Details on this estimation procedure are reported in tables 1-7 in the appendix. As a shorter lead time produces more significant results, we focus initially on a model estimated with a lead time of one quarter, but models with longer lead times have also been estimated. The estimated coefficients with a one quarter lead and the corresponding t-values (in parentheses) of the model which we shall henceforth call *model 1* are as follows:

$$(1) \quad Prob[failure] = \underset{}{9.55} - \underset{(-2.01)}{0.93CAP} - \underset{(-2.77)}{50.5ROA1} - \underset{(-3.25)}{0.059MOR/L} - \underset{(-1.83)}{0.094LIQ}$$

$$+ \underset{(1.98)}{1908.3ELOSS} + \underset{(1.79)}{8.4CONS}$$

All of the independent variables included in model 1 are significant at the 10 % test level. Model 1 includes indicators from every CAMEL group. CAP is the dominant measure of *Capital adequacy* when the lead time is one quarter and statistically significant at the 5 % test level. The negative sign suggests that a low capital adequacy ratio increases the probability of crisis. This is in line with our expectations. CAP is also strongly significant when the lead is two quarters (table 4 in the appendix). None of the two other indicators of capital adequacy (CCAP and L/E) are retained in any of the estimated models regardless of the lead time applied. Thus, CAP is the only indicator representing capital adequacy in model 1.

The share of residential lending, MOR/L, is included in model 1 as an indicator representing *Asset quality*. MOR/L is significant at a 1 % test level regardless of the lead time assumed. Thus, MOR/L seems to be a robust leading indicator of banking crisis. The negative sign implies that failed banks had a lower share of residential mortgages than other banks. This is in line with the experiences of the banking crisis in Norway at the beginning of the 1990s when the largest loan losses did not stem from the residential, but rather from the commercial loans.

The ratio of risk weighted assets to total asset (RWA/TA) is never statistically significant regardless of the length of the lead applied. The reason for this is that the other indicators of *Capital adequacy* and *Asset quality* are very significant and thus take the ground which RWA/TA was intended to cover. RWA/TA becomes statistically significant only when the other indicators representing *Capital adequacy* and *Asset quality* are excluded from the models.

Section 2.2 argues that high loan growth may reflect increased credit risk. The explanatory power of loan growth is checked for each of the three years prior to the date of risk evaluation. However, none of the loan growth indicators are included in model 1. The loan growth two years back is indeed statistically significant in some cases; when the lead time to failure is three quarters (LG2Y in table 5 in the appendix), three years back when the lead time is one quarter (LG3Y in table 1 in the appendix) or three years back when the lead time is two quarters (LG3Y in table 3 in the appendix). The sign of the estimated coefficients are negative, however. Thus, our data set reject the findings of Jiménez and Saurina (2006) and several other studies. One explanation could be that our sample period does not cover any severe banking crises. In addition, the relationship between loan growth and bank failure may be non-linear, because problems with adverse selection of borrowers only appear when the loan growth is exceptionally high. In fact, only three of the failed banks, namely Finansbanken, Kredittbanken and Enebakk Sparebank, experienced a credit growth which deviated substantially from the mean sample value. Finally, LG2, which measures the squared deviation from the average loan growth in the sample, is not statistically significant either.

The expected loss indicator (ELOSS) is statistically significant when the lead time to failure is one or two quarters. The sign of the coefficient is in line with our expectations, reflecting that higher expected losses increase the probability of failure. Thus, ELOSS is included as the second indicator representing *Asset quality* in model 1.

CONS is the only indicator representing *Management competence* in model 1. CONS is found to be statistically significant when the lead time is one or two quarters. The positive coefficient indicates that reduced concentration in the bank portfolio will make a failure less likely. This is in line with our expectations. The ratio of interest sensitive funding to total assets (ISF/TA) is found to be statistically significant when the lead time is three or four quarters. CONS and ISF/TA are however never retained together in any of the estimated models regardless of the lead time applied. Finally, the remaining *Management competence* indicator (SIZE) is never significant at the 10 % level, indicating that failing banks are not consistently bigger or smaller than their non-failed peers.

ROA1 is the only measure of *Earnings* in model 1. The alternative profit variable ROE1 is also significant when the lead time is one quarter (table 1 in the appendix), but with a positive coefficient that is counterintuitive. This is explained by the fact that ROE1 correlates strongly with ROA1. The inclusion of both indicators is thus causing multicollinearity and unreliable t-values. ROA1 is preferred at the expense of ROE1, based on the level of statistical significance and the sign of the coefficients. Moreover, as a high ROE1 may also reflect a low equity share, ROA1 is the preferable measure of profitability when monitoring the probability of bank failures. The two remaining indicators of return on capital are not found to be statistically significant in any of the regressions. The provisioning indicators (PROV and SPROV) and the actual loss indicator (LOSS) are not retained as statistically significant in the final model in any of the regressions. The interest rate margin (INTMARG) becomes statistically significant when the lead is four quarters, but the positive sign is not in line with our expectations that a high interest rate margin will increase profitability and thus reduce the probability of failure. Derviz and Podiera (2004) argue that banks with liquidity problems tend to raise their deposit rates in order to attract liquidity. However, the indicator measuring the deposit rate relative to the average deposit rate of the banks in the sample (DEPRATE) is not found to be statistically significant in any of the regressions. Thus, the positive sign of INTMARG that we find may be an artefact reflecting that all the failures in the present sample took place during a period when the interest rate margin was generally high in the Norwegian banking sector.[35] High interest margins may also result from more risky loan portfolios. Another explanation may be that problem banks tried to increase their declining profits by increasing the lending margins. This is in line with the negative relationship between interest rate margins and distance-to-default documented in the Euro area by Gropp et al. (2007).

Finally, the liquidity indicator of Norges Bank (LIQ) is the only indicator representing *Liquidity* in model 1. LIQ is statistically significant when observed one quarter before the event of failure, but not with longer lead times. The negative sign is in line with our expectations as an increase in the indicator

[35] The average interest margin during the last nine quarters of the estimation period was 0.22 percentage points below the average of the first eleven quarters.

means reduced liquidity risk and thus a lower probability of failure. When the lead time is two, three or four quarters *Liquidity* is represented by the ratio of deposits to gross lending DEP/L. The negative sign suggests that a higher DEP/L will reduce the probability of failure, as expected. Notice that the two liquidity indicators LIQ and DEP/L are never both statistically significant.

Altogether, model 1 comprises at least one indicator from each of the groups in the CAMEL system. MOR/L, CONS and ELOSS correlate significantly, but the high t-values and signs of the coefficients deny the suspicion of any serious multicollinearity problem. None of the remaining indicators in model 1 are highly correlated. Notice that model 1 does not include any of the indicators from the risk index currently used by Norges Bank. We can thus already conclude that the current risk index did not have optimal predictive power during the period 2000-2005. This confirms the need to re-estimate such a risk index at regular intervals.

4.3 Alternative versions of the risk index

As a second step in the process of identifying a recommended model it is stipulated that the model should include at most one indicator from each of the groups in the CAMEL system. This constraint gives us a more parsimonious model (from now on model 2) and circumvents any problems of multicollinearity. Model 1 includes only one indicator of *Capital adequacy* (CAP) and one indicator of *Liquidity* (LIQ). Thus, these two indicators are included in model 2. In terms of statistical significance, MOR/L is the best leading indicator of *Asset quality*. Thus, MOR/L is preferred at the expense ELOSS based on the level of statistical significance. When ELOSS is excluded, CONS becomes statistically insignificant. Thus, model 2 does not include any indicators of *Management competence.* When *model 2* is estimated using a lead length of one quarter the estimated coefficients and the corresponding t-values (in parentheses) are as follows (see table 8 in the appendix):

$$(2) \quad Prob[failure] = 12.38 - \underset{(-1.78)}{0.69CAP} - \underset{(-3.14)}{48.43ROA1} - \underset{(-3.68)}{0.063MOR/L} - \underset{(-1.74)}{0.07LIQ}$$

All the indicators in model 2 are statistically significant at the 10 % test level. The signs of the coefficients are also in line with the ex ante expectations, indicating that deteriorating levels of capital adequacy (CAP), asset quality (MOR/L), earnings (ROA1) and liquidity (LIQ) are associated with a higher probability of failure.

The estimated coefficients and t-values of models 1 and 2 do not appear to depend systematically on the length of the lead time. As reported in table 9 the coefficients of the indicators representing *Capital Adequacy*, *Asset quality, Management competence* and *Liquidity* are stable across the different lead times. In addition, the t-values of these indicators remain relatively high when the lead time increases.

Thus, the indicators representing *Capital Adequacy*, *Asset quality*, *Management competence* and *Liquidity* seem to be able to capture the fragility of individual banks at an early stage. However, the *Earnings* indicator does not become statistically significant until the problems materialise in terms of depressed earnings. The predictive power of the *Earnings* indicator is still acceptable, especially when taking into account that we have set the date of failure at a very early stage of the crisis (the first sign of insolvency and/or illiquidity documented by the FSA).

Table 9

Model	Lag length	Constant	CAP	MOR/L	LIQ	ROA1	ELOSS	CONS
Model 1	1 quarter	9.55 (1.66)	-0.93 (-2.01)	-0.059 (-3.25)	-0.094 (-1.83)	-50.48 (-2.77)	1908.3 (1.98)	8.37 (1.79)
	2 quarters	6.07 (1.50)	-0.68 (-2.04)	-0.049 (-3.20)	-0.075 (-1.86)	-15.31 (-0.51)	1712.8 (1.96)	6.84 (1.57)
	3 quarters	5.21 (1.35)	-0.53 (-1.74)	-0.053 (-3.44)	-0.081 (-1.98)	-34.44 (-1.62)	1742.2 (2.02)	6.86 (1.54)
	4 quarters	6.35 (1.61)	-0.58 (-1.92)	-0.060 (-3.74)	-0.099 (-2.43)	-14.89 (-0.39)	2004.7 (2.25)	8.58 (1.88)
Model 2	1 quarter	12.38 (2.48)	-0.69 (-1.78)	-0.063 (-3.68)	-0.070 (-1.74)	-48.43 (-3.14)		
	2 quarters	9.38 (2.63)	-0.49 (-1.82)	-0.057 (-3.99)	-0.062 (-1.76)	-5.98 (-0.18)		
	3 quarters	8.61 (2.48)	-0.39 (-1.59)	-0.060 (-4.29)	-0.062 (-1.74)	-28.51 (-1.29)		
	4 quarters	10.00 (2.87)	-0.41 (-1.69)	-0.065 (-4.40)	-0.075 (-2.08)	-2.88 (-0.06)		

In order choose between models 1 and 2 we look at the Pseudo R^2, which is recommended by McFadden (1979) for measuring the explanatory power of logit models. The definition is as follows: Pseudo $R^2 = 1 - \frac{L_1}{L_0}$, where L_0 and L_1 are the constant-only and the full model log likelihoods, respectively. Model 1 obtains a value of $1 - \frac{-23.86}{-54.33} = 0.561$. Model 2 obtains a slightly lower value at 0.524[36]. Thus, model 1 has a higher explanatory power than model 2 in terms of Pseudo R^2. A drawback to Pseudo R^2 is that this measure does not impose any penalty on the number of independent variables added to the model. An alternative measure of explanatory power is the Akaike Information Criterion (AIC) which is defined in the following way:

$$AIC = -2loglikelihood + 2n$$, where n is the number of parameters estimated.

The AIC penalizes over-parameterized models severely.[37] A low AIC indicates that the explanatory power is high. Model 1 has a slightly lower AIC (61.71) than the more parsimonious model 2 (61.76). Thus, the gain from a better fit is dominating the penalty from including two extra variables in model 1 (ELOSS and CONS). Our preliminary conclusion is that model 1 should be preferred.

Finally, it is an interesting experiment to compare the explanatory power of models 1 and 2 with the model of Berg and Hexeberg. This model estimated on the current sample (from now on *model 3*) with the four indicators and a lead time of one quarter is as follows (see table 9 in the appendix):

[36] Pseudo $R^2 == 1 - \frac{-25.88}{-54.33} = 0.524$

[37] See for instance Harvey (1981)

(3) $\quad Prob[failure] = -20.66 + 0.343L / E + 7.86CIL / RA + 4.00ISF / TA + 8.37C / I$

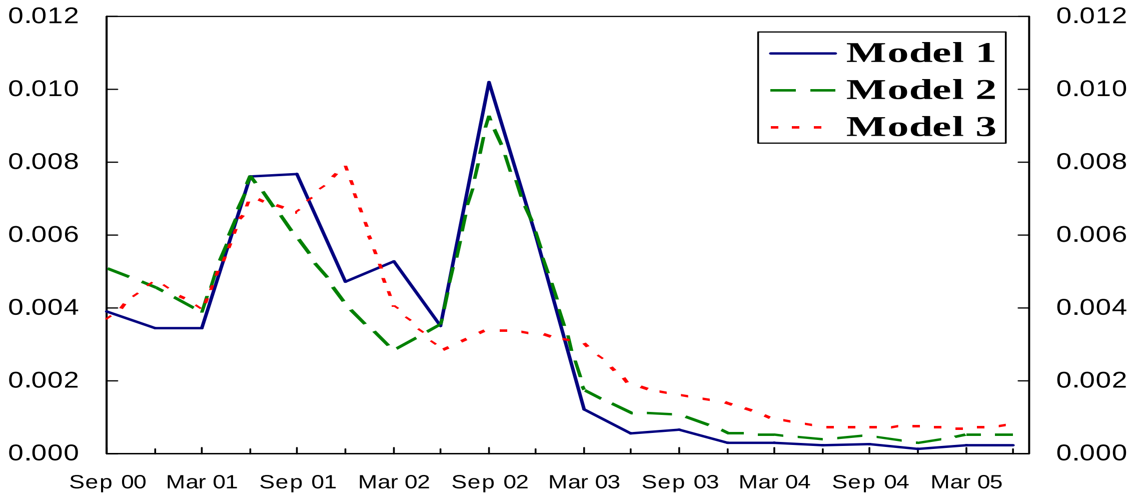
(2.59) (4.61) (1.68) (2.38)

All the indicators in model 3 are statistically significant at the 10 % test level. As opposed to the corresponding regression in Berg and Hexeberg's analysis (lead times between 0 and 4 months), the ratio of interest sensitive funding to total assets are statistically significant in our sample. The three remaining indicators were also statistically significant in Berg and Hexeberg's analysis. Moreover, the signs of the coefficients are as expected. The Pseudo R^2 and AIC of model 3 is 0.311[38] and 84.85 respectively. Thus, the explanatory power of model 3 in terms of Pseudo R^2 and AIC is substantially lower than the explanatory power of the models 1 and 2. This reconfirms that the current risk index did not have optimal predictive powers during the period 2000-2005.

5. In-sample predictive powers

In order to evaluate the predictive power of model 3 compared to the two new models (1 and 2) we track the failure probabilities produced by the models within the estimation period. Models with a lead time of one quarter are used, confer sections 4.2 and 4.3. We look at whether the models are able to produce early and strong signals prior to the date of actual failures, but also at whether the models produce any false alarms. In chart 1 the average failure probabilities from each of the three models are plotted against the time axis:

Chart 1 Mean probabilities of bank failures 2000-2005



The mean probabilities of failure generally exhibit the same development for all models until 2002Q3. But in the last two quarters of 2002 the failure probabilities according to models 1 and 2 are

[38] Pseudo $R^2 = 1 - \frac{-37.43}{-54.33} = 0.311$

considerably higher than the probabilities from model 3. From 2003 onwards the probabilities of failure generated by models 1 and 2 are below those of model 3. As seven of the eight actual failures in the sample took place during 2002 (the remaining failure, in Sparebanken Rana, took place in 2003Q1), we can perhaps say that the two new models, and especially model 1, produce stronger signals prior to the failures and the appropriate weaker signals after the failed banks are removed from the sample.

In order to get a more detailed picture of the predictive properties of the three models, we look at the signals produced prior to each of the eight actual failures. Charts 2-9 below display the probabilities of failure generated by the three models for each quarter from 2000Q3 until the last quarter prior to the date of failure. As displayed in the charts 2 and 3 below, model 2 exhibit substantially better predictive powers than the two other models before the failures of Finansbanken and Nesset Sparebank. Model 2, but also model 1, produces strong signals already six quarters prior to the failure of Finansbanken (chart 2). Notice that Finansbanken is the second largest failed bank in our sample. However, all models display disappointing predictive powers prior to the failure of Nesset Sparebank (chart 3). The explanation seems to be that the reported capital adequacy of Nesset Sparebank fell and the return on assets deteriorated only immediately before failure took place.

Chart 2 Finansbanken

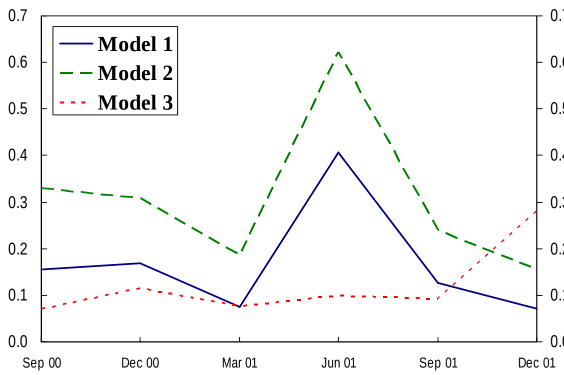
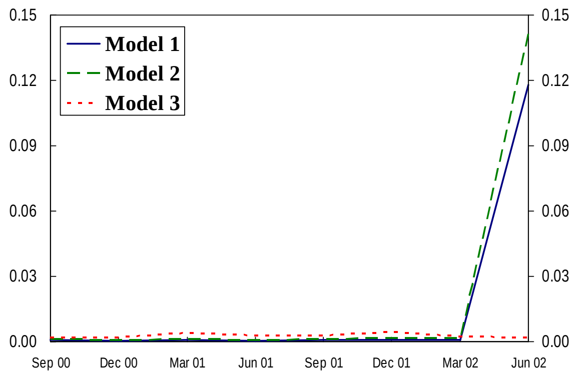


Chart 3 Nesset Sparebank



Model 1 predicts the failures of Helgeland Sparebank, Kredittbanken, Sparebanken Flora-Bremanger, Sparebanken Rana and Enebakk Sparebank in a more convincing manner than models 2 and 3. Model 1 produces early, but weak signals prior to the failure of Helgeland Sparebank (chart 4), whereas the other two models do not appear to provide signals. Model 1 also produces very high probabilities of failure for Kredittbanken and Sparebanken Flora-Bremanger (charts 5 and 6). However, all the three models fail to signal the failure of Sparebanken Flora-Bremanger at an early point in time. Just prior to the crisis the probability estimated from model 1 increases strongly. The explanation seem to be that the capital adequacy of Sparebanken Flora-Bremanger fell, the return on assets deteriorated, and the liquidity indicator fell only immediately before failure occurred. Finally, model 1 outperforms model 2 and 3 in predicting the failures of Sparebanken Rana and Enebakk Sparebank (charts 7 and 8).

Chart 4 Helgeland Sparebank

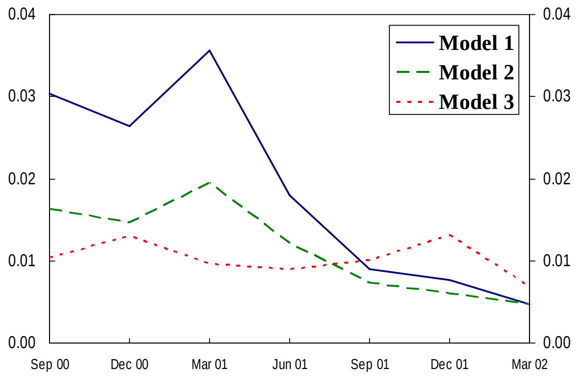


Chart 5 Kredittbanken

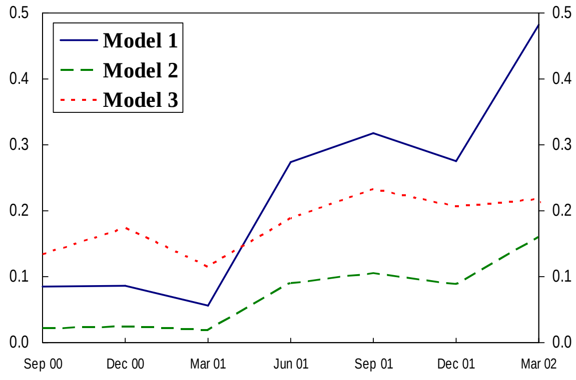


Chart 6 Sparebanken Flora-Bremanger

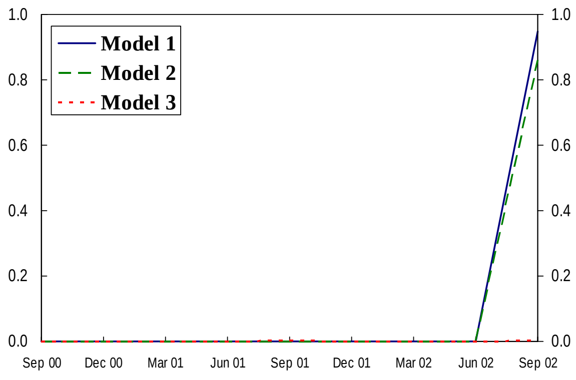


Chart 7 Sparebanken Rana

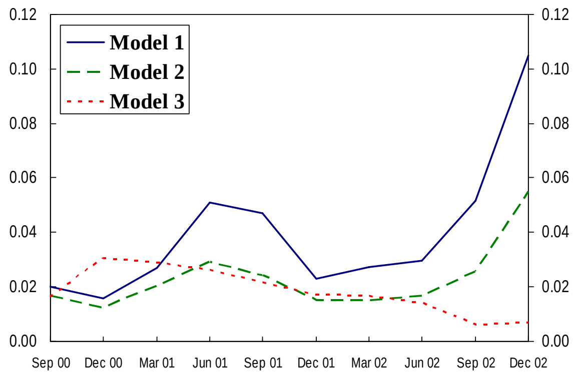
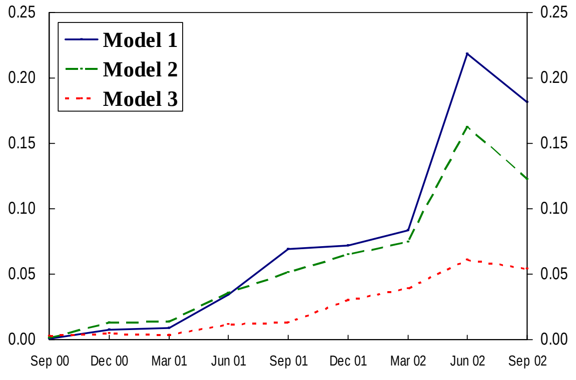
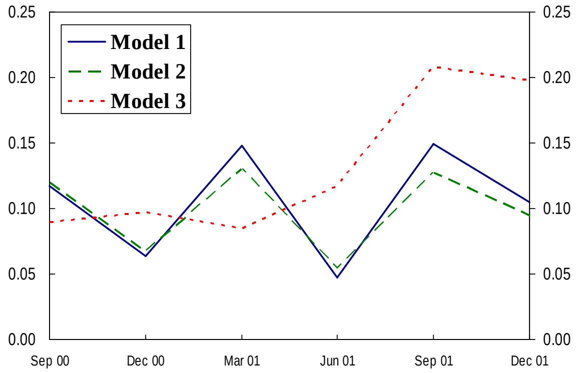


Chart 8 Enebakk Sparebank



As Nordlandsbanken is the largest failed bank in our sample we are particularly interested in the models' predictive powers in this case. We find that model 3 exhibits better predictive powers than the two other models before the failure of Nordlandsbanken (chart 9). High and increasing values on gross lending (L/E) and in particular commercial lending (CIL/RA) drives the probability of failure in model 3, but interest sensitive funding (ISF/TA) and cost-income ratio (C/I) are also higher than the average of our sample. Notice, however, that models 1 and 2 also produce strong and early signals prior to the failure of Nordlandsbanken. A relatively low capital adequacy ratio (CAP) at around 10 percent, a low share of mortgage lending (MOR/L) at around 30 per cent and low liquidity (LIQ) are the main factors behind the fairly high probabilities of failure produced by these two models. In the case of model 1, high expected losses (ELOSS) is also a contributor to high probabilities of failure, whereas an extremely low concentration in the loan portfolio (CONS) pulls in the opposite direction.

Chart 9 Nordlandsbanken



Altogether, we conclude from the inspection of the eight actual failures that the two new models (model 1 and 2) have better predictive powers than the risk index currently at work in Norges Bank (model 3). The predictive properties of model 1 seem, in turn, slightly better than the properties of model 2, which is in line with the conclusion from the model selection criteria AIC and Pseudo R^2.

As a third check we shall consider the extent of Type 1 errors (the failure to predict an actual failure) and Type 2 errors (a false prediction of failure) of the three different models. In the practical use of early warning systems a threshold must be set on the probability of failure in order to distinguish between problem banks, which should be analysed in more detail, and banks with a low probability of failure. Lowering the threshold to allow more banks to be picked up, and thereby reducing the Type 1 errors, necessarily raises the frequency of false alarms (Type 2 errors). As most supervisors prefer investigating too many banks instead of too few, Type 1 errors are normally perceived as more serious than Type 2 errors. Thus, the probability threshold is normally set relatively low. However, supervisors with relatively stable financial systems may have a stronger preference for avoiding Type 2 errors that induce costly and undue intervention.[39]

We look at probabilities of failure one quarter before the event. Initially we somewhat arbitrarily set the probability threshold at 0.02, which is slightly lower than for instance Demirgüç-Kunt and Detragiache (1998) whose cut off probability is 0.05.[40] Model 1 produces probabilities of failure above 0.02 for all the eight failed banks in our sample, implying zero Type 1 errors. Model 2 delivers one Type 1 error as the failure probability of Helgeland Sparebank never exceeds 0.02. In comparison,

[39] See Davis and Karim (2007)
[40] They decide this threshold on the basis of frequency of crisis episodes in their sample.

model 3 produces three Type 1 errors, because the signals prior to the failures of Helgeland Sparebank, Nesset Sparebank and Sparebanken Flora-Bremanger are not strong enough.

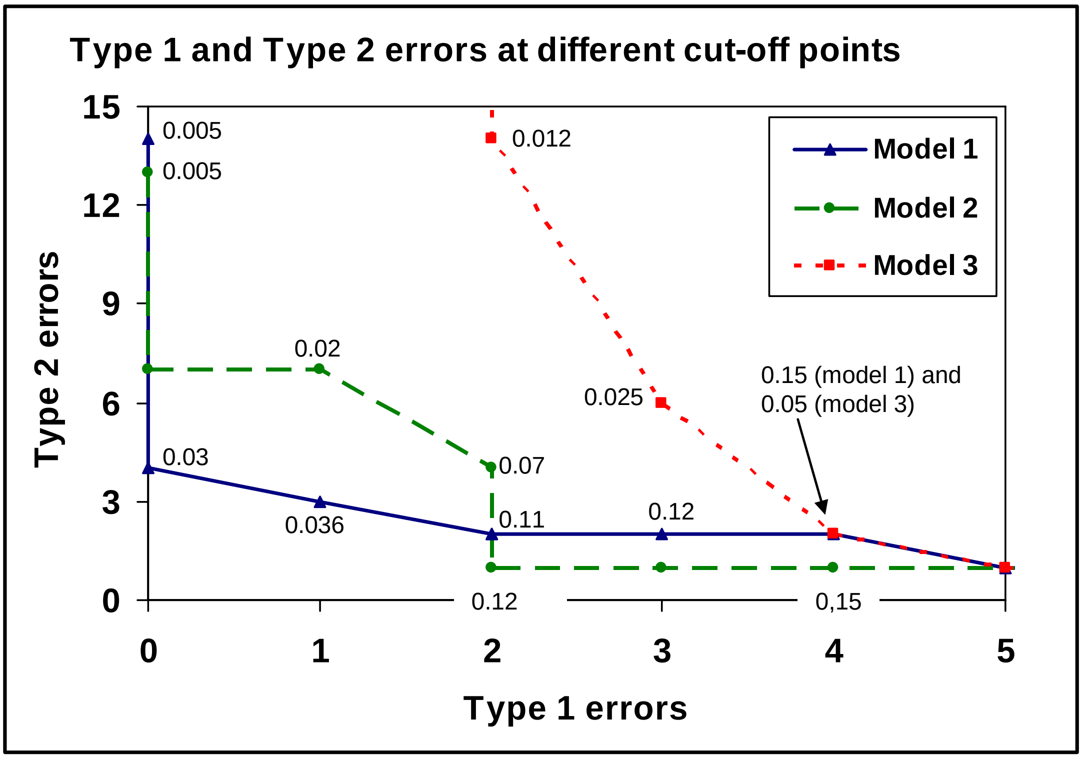
As mentioned above Type 2 errors (false alarms) are normally perceived as less serious than Type 1 errors. Type 2 errors can include banks which were vulnerable to negative shocks, making it rational to take pre-emptive policy action, even if this action may be perceived as unnecessary in hindsight. Models 1 and 2 produce five[41] and seven[42] Type 2 errors respectively. The number of false alarms is not very high considering the size of our sample. In addition, some of these banks were close to being classified as failed. Sparebanken Sogn og Fjordane merged with a bank that later failed, namely Sparebanken Flora-Bremanger. Sandnes Sparebank was the parent bank of Acta Bank, who had serious difficulties due to some costly and unprofitable investments in an IT system. Finally, the current risk index (model 3) produces seven Type 2 errors.[43]
Looking at the noise-to-signal-ratio[44] the score of model 3 is 0.088[45]. Model 1 receives a ratio at 0.039[46], while model 2 gets a ratio at 0.063[47]. Altogether, model 1 outperforms model 2 and 3 with 100 per cent of the crisis episodes being called correctly and only around 4 percent of the surviving banks being wrongly classified. Furthermore, model 2 beats model 3 in terms of noise-to-signal-ratio and Type 1 and Type 2 errors.

The cut-off probability used above is arbitrary, and we therefore look in more detail at the performance of the three models in terms of Type 1 errors and Type 2 errors in Chart 10. The chart shows how errors in each model depend on the cut-off points used. The curves exhibit the normal concave shape with a trade-off between Type 1 and Type 2 errors. The preferred model should have a curve close to the lower left corner of the chart. The chart shows that model 3 never performs better than model 1 and model 2. When the probability threshold is set below 0.1, model 1 performs better than model 2. When the probability threshold is higher than 0.11 the opposite is true. The models produce the same number of Type 1 and Type 2 errors when the threshold for models 1, 2 and 3 is set at 0.25, 0.16 and 0.07 respectively. Models 1 and 3 also produces the same number of errors 1 and 2 when the threshold is set at 0.15 and 0.05, respectively. These thresholds can, however, not represent optimal cut-off points as the numbers of Type 1 errors are too high. When the numbers of Type 1

[41] Bank 1 Oslo, Nordea, Sandnes Sparebank, Sunndal Sparebank and Totens Sparebank.
[42] Bank 1 Oslo, Fokus Bank, Nordea, Sandnes Sparebank, Sparebanken Nord-Norge, Sunndal Sparebank and Totens Sparebank.
[43] Bank 1 Oslo, Cultura Sparebank, Halden Sparebank, Nes Prestegjelds Sparebank, Sandnes Sparebank, Totens Sparebank and Sparebanken Nord-Norge
[44] Noise-to-signal ratio = (the probability of type 2 errors at a given threshold)/(1- the probability of type 1 errors at a given threshold)
[45] Noise-to-signal ratio = (7/128)/[1-(3/8)] = 0.0875
[46] Noise-to-signal ratio = (5/128)/[1-(0/8)] = 0.0625
[47] Noise-to-signal ratio = (7/128)/[1-(1/8)] = 0.0391

errors are below two, the curve of model 1 lies closer down to the left corner than the other curves, reflecting that model 1 is better at predicting bank failures than model 2 and 3.

Chart 10



In the case of model 1, probability thresholds between 0.03 and 0.12 seems to produce a low number of Type 1 errors at the same time as the number of false alarms (Type 2 errors) is not too high (see table 10 in the appendix). A threshold at 0.03 results in a noise-to-signal-ratio of 0.031, whereas a threshold at 0.12 gives a ratio at 0.025. The noise-to-signal-ratio increases outside this interval. The noise-to-signal-ratio does not, however, take into account the low number of failed banks in our sample. Given that very few banks failed, Type 1 errors should probably be punished more heavily in the noise-to-signal-ratio formula. Thus, unless policy makers have a strong desire to avoid unnecessary intervention cost, a cut-off point at 0.03 could be chosen in order to optimize the predictive powers of model 1.

6. Out of sample predictions

In order to further assess the forecasting accuracy of the three models we also look at their predictive power using a set of banks that failed prior to our estimation period. This set of failed banks is from the Norwegian banking crisis 1988-93. By doing this, we ensure that the selected indicators have acceptable predictive powers during a severe banking crisis. Due to limitations on available data, in particular for the years prior to 1991, it is not possible to include all the banks that failed during the period 1988-93. But data are available on the following 11 banks:

Table 10

<table>
<tr><th>Bank</th><th>Failure event 1 (first signal)</th><th>Failure event 2</th><th>Gross lending 1990Q2 (MNOK)</th></tr>
<tr><td>Halsa Sparebank</td><td rowspan="4">Sought assistance from the insurance fund (1991Q1)</td><td>Sought liquidity support from Norges Bank (1991Q2)</td><td>133</td></tr>
<tr><td>Nittedal Sparebank</td><td>Sought liquidity support from Norges Bank (1991Q4)</td><td>325</td></tr>
<tr><td>Nore Sparebank</td><td></td><td>164</td></tr>
<tr><td>Tysfjord Sparebank</td><td>Sought liquidity support from Norges Bank (1991Q1)</td><td>121</td></tr>
<tr><td>Christiania Bank og Kreditkasse</td><td>Sought assistance from the insurance fund (1991Q2)</td><td></td><td>80098</td></tr>
<tr><td>Spb Rogaland</td><td rowspan="3">Sought assistance from the insurance fund (1991Q3)</td><td>Sought liquidity support from Norges Bank (1991Q3)</td><td>12789</td></tr>
<tr><td>Spb Midt-Norge</td><td></td><td>14917</td></tr>
<tr><td>DnB Bank</td><td>Sought liquidity support from Norges Bank (1991Q4)</td><td>138943</td></tr>
<tr><td>Hof Sparebank</td><td>Sought assistance from the insurance fund (1992Q2)</td><td></td><td>164</td></tr>
<tr><td>Oslobanken</td><td rowspan="2">Sought liquidity support from Norges Bank (1992Q3)</td><td>Sought assistance from the insurance fund (1993Q2)</td><td>4221</td></tr>
<tr><td>Samvirkebanken</td><td>Sought assistance from the insurance fund (1993Q1)</td><td>1771</td></tr>
</table>

Den norske Bank was the largest bank in Norway and as reported in the right column in table 4, it was by far the largest of the 11 failed banks in terms of gross lending. By June 1990, the gross lending of Christiania Bank og Kreditkasse amounted to 57.6 per cent of the gross lending of Den norske Bank, whereas the size of Sparebanken Rogaland and Sparebanken Midt-Norge amounted to 9.2 and 10.7 per cent, respectively, of Den norske Bank. The remaining seven failed banks in the sample were far smaller.

Even with this reduced set of failed banks, some approximations of data are necessary. Some of the quarterly balance sheet data are constructed by interpolation from less frequent data (three reports per year), and risk weighted assets are approximated by multiplying identified exposures with the corresponding risk weights as defined by the Basel accord. Finally, the date of failure is set equal to the date when the bank applied for assistance from the insurance fund or liquidity support from Norges Bank (the first of these two events). Notice that this definition of failure deviates from the one used in earlier sections of this paper. The feasible sample of failed banks from the banking crisis would have been substantially smaller if the date of failure was set at an earlier point in time, because of more severe data limitations.

We look at the predictive powers of all of the three models (1, 2 and 3). Charts 11-21 below display the probabilities of failure generated by the three models for each quarter from 1990Q1 until the last quarter prior to the date of failure. Charts 11 and 12 shows that model 2 outperforms model 1 and 3 in terms of predicting the failures of Den norske Bank and Oslobanken. In these cases, model 2 produces strong signals already two years before the banks failed. Model 2 produces extremely high probabilities of failure for these two banks, close to 1.0 for Oslobanken and 0.85 for Den norske Bank. The two other models also provide strong and early signals of these two failures. Model 1 produces a probability of failure close to 1.0 around one year before the crisis in Oslobanken, and a crisis probability at around 0.83 two quarters before the date of failure in Den norske Bank. Model 3 also produces strong and early signals prior to the failures of Den norske Bank and Oslobanken. Thus, all of the three models give high probabilities of failure for the largest bank in the sample, namely Den norske Bank.

Chart 11 Den norske Bank

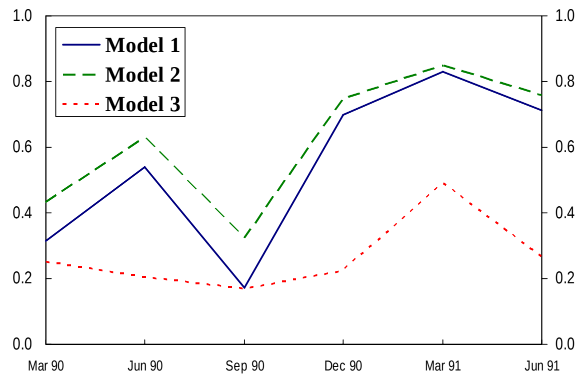
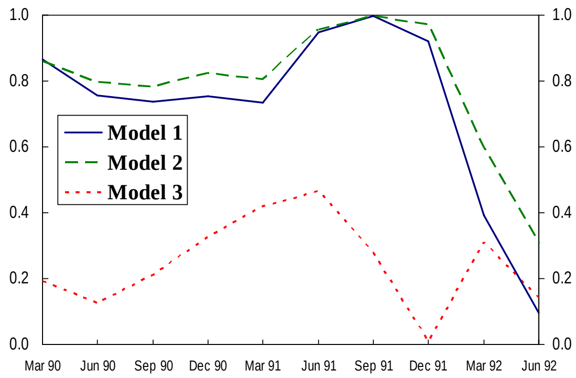


Chart 12 Oslobanken



For five of the 11 failed banks, model 1 displays significantly better forecasting accuracy than the two other models (see charts 13-17). The predictive ability of model 1 is particularly convincing in the case of Tysfjord Sparebank. In this case, model 1 delivers a probability of failure above 0.5 for all the four quarters immediately prior to the failure, including a probability close to 1.0 in the last quarter. In addition, model 1 is strongly signalling the failures of Nore Sparebank, Samvirkebanken and Hof Sparebank (probabilities close to 1.0). Model 2 also sends strong signals before the failure of Nore Sparebank, Tysfjord Sparebank, Samvirkebanken and Hof Sparebank, but these signals appear at a later stage than the signals from model 1.

Chart 13 Tysfjord Sparebank

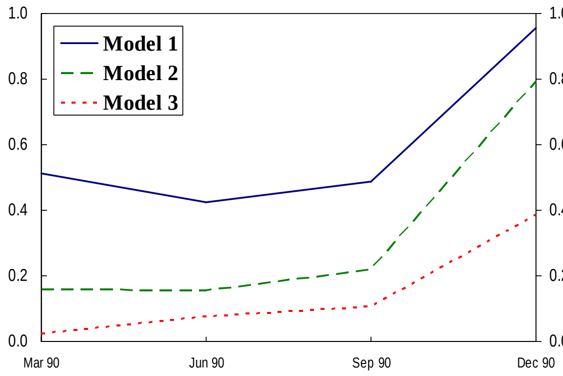


Chart 14 Nore Sparebank

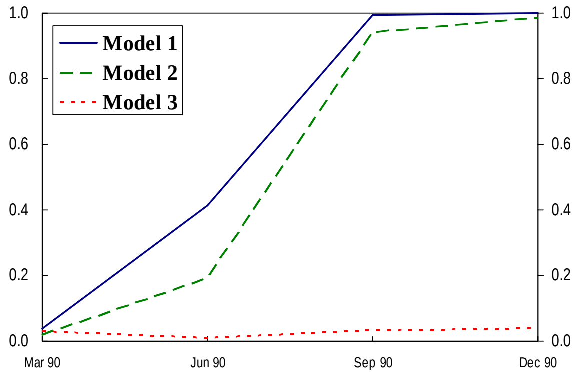


Chart 15 Halsa Sparebank

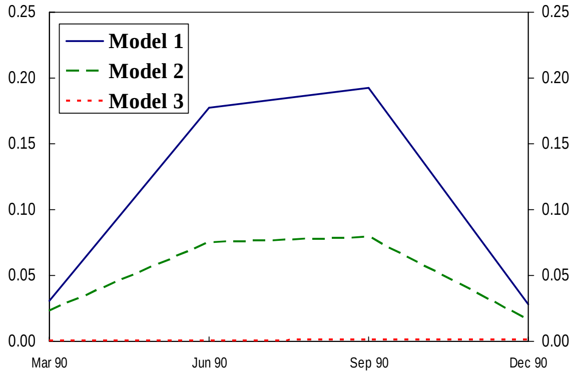


Chart 16 Samvirkebanken

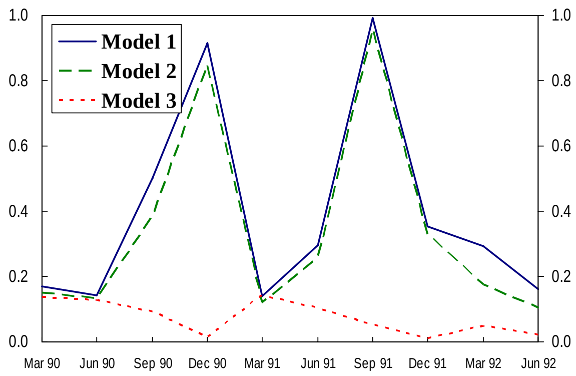
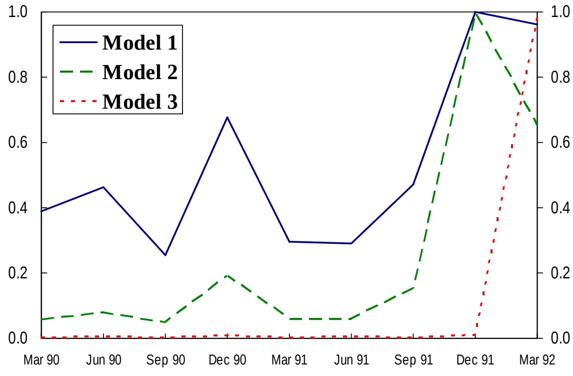
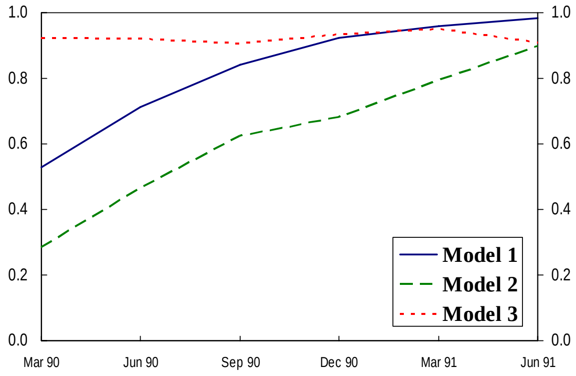


Chart 17 Hof Sparebank



We should expect model 3 to predict the 11 failures fairly well as all of these banks were included in the sample on which Berg and Hexeberg based their recommendation. However, model 3 only outperforms model 1 and 2 in one single case, namely in predicting the failure of Sparebanken Midt-Norge. But models 1 and 2 also provide strong and early signals in this case.

Chart 18 Sparebanken Midt-Norge



For three out of the 11 failed banks the predictive powers of the three models is on approximately the same level (charts 19, 20 and 21). While model 3 provides some weak early signals of the future failure of Nittedal Sparebank, models 1 and 2 produce a monotonic increase in the probability of failure one quarter prior to the date of failure. All three models give strong warnings more than a year before the failure of Sparebanken Rogaland. In the case of Christiania Bank og Kreditkasse, all three models are signalling strongly, but only a fairly short time before the actual failure. The strong signals are reassuring as Christiania Bank og Kreditkasse is the second largest bank in our sample of failed banks from the 1988-93 period.

Chart 19 Nittedal Sparebank

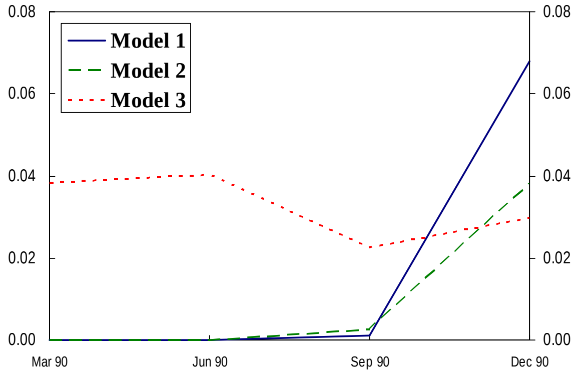


Chart 20 Sparebanken Rogaland

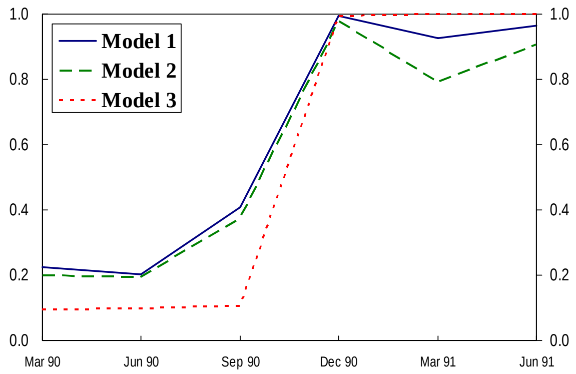
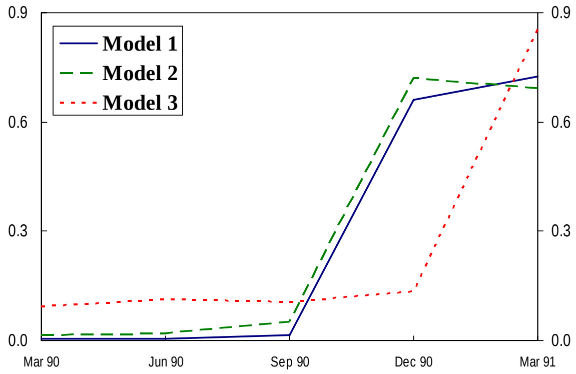


Chart 21 Christiania Bank og Kreditkasse



In order to consider Type 2 errors, data would have to be constructed for all the surviving banks during the period 1988-93. The gain from carrying out this substantial work is not considered worthwhile. However, Type 1 errors are possible to calculate based on the analysis above. With a probability threshold at 0.03 neither model 1 nor model 2 would have delivered any Type 1 errors. On the contrary model 3 would produce one Type 1 error as the probabilities never exceed the 0.03 threshold in the case of Halsa Sparebank. As model 3 gives probabilities just above 0.04 in the case of Nore Sparebank and Nittedal Sparebank, the number of Type 1 errors will increase with a slightly higher threshold. Thus, models 1 and 2 display substantially better predictive powers than model 3 outside the estimation period. While model 1 outperforms model 2 in the cases of Nittedal Sparebank, Nore Sparebank, Tysfjord Sparebank, Halsa Sparebank, Hof Sparebank, Sparebanken Midt-Norge, Samvirkebanken and Sparebanken Rogaland, the opposite is the case for Oslobanken, Den norske Bank og Christiania Bank and Kreditkasse. Notice that model 2 thus performs better for the two largest failed banks (Den norske Bank and Christiania Bank og Kreditkasse). But the forecasting power of model 1 is also very good in these two cases, and the difference in the ability to predict the failures of the two largest banks is not significant. Altogether, model 1 shows better classification accuracy than models 2 and 3, both within and outside the estimation period. Consequently, we recommend that the re-estimated risk index to be used by Norges Bank should be based on model 1.

7. Conclusion

In 1994 the risk index used by Norges Bank was reconstructed based on research by Sigbjørn Atle Berg and Barbro Hexeberg. Using the Norwegian bank crisis of 1988-1993 as their estimation period they concluded that it would be sufficient to include four indicators in the risk index. The risk index comprising these four indicators has been left unchanged since 1994. Meanwhile, the banking sector has experienced substantial structural changes. Thus, the need to re-estimate the risk index is clearly present. In this paper a logit model is estimated based on data from 2000-2005. In competition with 23 new indicators none of the four indicators from the current risk index become part of a new recommended risk index. Our data set also does not confirm the findings of Jiménez and Saurina

(2006) and several other studies that high loan growth is an indicator of increased credit risk. One explanation could be that our sample period does not cover any severe banking crises.

The predictive properties of two new risk indices (models 1 and 2) are tested together with a version of the current risk index (model 3) within the estimation period. In order to ensure that the chosen indicators can also provide relevant warnings during a deeper bank crisis the predictive powers are tested outside the estimation period on 11 failed banks from the period 1990-93. Models 1 and 2 both exhibit better classification accuracy than model 3, within and outside the sample period. The recommended risk index (model 1) gives strong and early signals well before the crisis culminates in all the 11 failed banks. The recommendation resulting from the econometric analysis is therefore that the risk index should include the following six indicators with the coefficient values given in equation (1):

(1) The capital adequacy ratio (*Capital adequacy*)
(2) The ratio of Residential mortgages to Gross lending (*Asset quality*)
(3) The expected loss measure (*Asset quality*)
(4) The concentration risk measure (*Asset quality*)
(5) The return on assets (*Earnings*)
(6) Norges Bank's liquidity indicator (*Liquidity*)

This risk index seems able to predict failures and provide valuable information about troubled banks with sufficient lead time to allow preventive or remedial actions at problem banks to be taken. The risk index should, however, be used in conjunction with market indicators, macroeconomic indicators and qualitative information to assess and understand what vulnerabilities and potential shocks are most threatening at any time. Moreover, future changes in the economic environment, the composition of the banking sector and the regulatory framework will gradually make even this risk index outdated. Practical use of the re-estimated risk index may also reveal weaknesses attached to the index which should taken into account when updated versions of the risk index are constructed in the future.

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9. Appendix

Table 1 One quarter lead time. Variables with counterintuitive signs included

```
CS(10) Modelling Failure by Logit
       The estimation sample is 1 - 2622

                  Coefficient  Std.Error  t-value  t-prob
Constant             -28.3495      17.80    -1.59   0.111
CAP                  -1.93468     0.8818    -2.19   0.028
ROE1                  84.8595      37.27     2.28   0.023
ROA1                 -1216.53      510.5    -2.38   0.017
SPROV                -5.55206      2.515    -2.21   0.027
MOR/L               -0.174072    0.06095    -2.86   0.004
LIQ                 -0.300052     0.1449    -2.07   0.038
ELOSS                 23185.2      9783.     2.37   0.018
CONS                  115.794      47.72     2.43   0.015
DEP/L               -0.275468     0.1648    -1.67   0.095
LG3Y                -0.462498     0.2142    -2.16   0.031

log-likelihood    -10.0513033  no. of states              2
no. of observations      2622  no. of parameters         11
baseline log-lik    -54.32579  Test: Chi^2( 10)      88.549 [0.0000]**
AIC                42.1026066  AIC/n           0.0160574396
mean(Failure)      0.00305111  var(Failure)       0.0030418
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

*** Warning: there is quasicomplete separation.
The maximum likelihood estimates are not unique,
and 1161 observations have P(observed state)=1.

              Count   Frequency Probability    loglik
State 0        2614     0.99695     0.99695    -3.370
State 1           8     0.00305     0.00305    -6.681
Total          2622     1.00000     1.00000    -10.05
```

Table 2 Model 1 (one quarter lead time). Variables with counterintuitive signs excluded

```
CS(14) Modelling Failure by Logit
       The estimation sample is 1 - 2622

                  Coefficient  Std.Error  t-value  t-prob
Constant              9.55044      5.739     1.66   0.096
CAP                 -0.934663     0.4654    -2.01   0.045
ROA1                 -50.4760      18.21    -2.77   0.006
MOR/L              -0.0587961    0.01808    -3.25   0.001
LIQ                -0.0938503    0.05127    -1.83   0.067
ELOSS                 1908.26      963.7     1.98   0.048
CONS                  8.37154      4.679     1.79   0.074

log-likelihood    -23.8569313  no. of states              2
no. of observations      2622  no. of parameters          7
baseline log-lik    -54.32579  Test: Chi^2(  6)      60.938 [0.0000]**
AIC                61.7138625  AIC/n           0.0235369422
mean(Failure)      0.00305111  var(Failure)       0.0030418
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        2614     0.99695     0.99695    -6.705
State 1           8     0.00305     0.00305    -17.15
Total          2622     1.00000     1.00000    -23.86
```

Table 3 Two quarters lead time. Variables with counterintuitive signs included

CS(53) Modelling Failure by Logit
The estimation sample is 1 - 2614

	Coefficient	Std.Error	t-value	t-prob
Constant	-0.232019	4.488	-0.0517	0.959
CAP	-0.982320	0.4118	-2.39	0.017
MOR/L	-0.0704007	0.01803	-3.90	0.000
ELOSS	4292.89	1571.	2.73	0.006
CONS	21.5510	8.290	2.60	0.009
DEP/L	-0.0892218	0.03929	-2.27	0.023
LG3Y	-0.0996847	0.04455	-2.24	0.025

log-likelihood	-29.2559472	no. of states	2
no. of observations	2614	no. of parameters	7
baseline log-lik	-54.30131	Test: Chi^2(6)	50.091 [0.0000]**
AIC	72.5118944	AIC/n	0.0277398219
mean(Failure)	0.00306044	var(Failure)	0.00305108

Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

	Count	Frequency	Probability	loglik
State 0	2606	0.99694	0.99694	-7.033
State 1	8	0.00306	0.00306	-22.22
Total	2614	1.00000	1.00000	-29.26

Table 4 Two quarters lead time. Variables with counterintuitive signs excluded

CS(54) Modelling Failure by Logit
The estimation sample is 1 - 2614

	Coefficient	Std.Error	t-value	t-prob
Constant	3.26053	3.875	0.841	0.400
CAP	-0.675714	0.3321	-2.03	0.042
MOR/L	-0.0521928	0.01604	-3.25	0.001
ELOSS	1580.48	850.8	1.86	0.063
CONS	7.65922	4.501	1.70	0.089
DEP/L	-0.0592390	0.03210	-1.85	0.065

log-likelihood	-32.5246136	no. of states	2
no. of observations	2614	no. of parameters	6
baseline log-lik	-54.30131	Test: Chi^2(5)	43.553 [0.0000]**
AIC	77.0492271	AIC/n	0.0294756033
mean(Failure)	0.00306044	var(Failure)	0.00305108

Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

	Count	Frequency	Probability	loglik
State 0	2606	0.99694	0.99694	-7.586
State 1	8	0.00306	0.00306	-24.94
Total	2614	1.00000	1.00000	-32.52

Table 5 Three quarters lead time. Variables with counterintuitive signs included

```
CS(66) Modelling Failure by Logit
       The estimation sample is 1 - 2606

                  Coefficient  Std.Error  t-value  t-prob
Constant              3.57533      3.590    0.996   0.319
MOR/L              -0.0748671    0.02062    -3.63   0.000
ELOSS                 3687.45      1466.     2.52   0.012
DEP/L               -0.129472    0.04179    -3.10   0.002
CIL/RA               -14.3589      6.526    -2.20   0.028
ISF/TA                6.89304      2.989     2.31   0.021
LG2Y               -0.0827579    0.04179    -1.98   0.048

log-likelihood    -29.1298602  no. of states              2
no. of observations      2606  no. of parameters          7
baseline log-lik    -54.27675  Test: Chi^2(  6)      50.294 [0.0000]**
AIC                72.2597203  AIC/n            0.027728212
mean(Failure)      0.00306984  var(Failure)      0.00306041
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        2598     0.99693     0.99693    -7.046
State 1           8     0.00307     0.00307    -22.08
Total          2606     1.00000     1.00000    -29.13
```

Table 6 Three quarters lead time. Variables with counterintuitive signs excluded

```
CS(69) Modelling Failure by Logit
       The estimation sample is 1 - 2606

                  Coefficient  Std.Error  t-value  t-prob
Constant             0.751186      1.745    0.430   0.667
MOR/L              -0.0536340    0.01349    -3.98   0.000
DEP/L              -0.0823885    0.02673    -3.08   0.002
ISF/TA                6.54401      2.913     2.25   0.025

log-likelihood    -33.2843035  no. of states              2
no. of observations      2606  no. of parameters          4
baseline log-lik    -54.27675  Test: Chi^2(  3)      41.985 [0.0000]**
AIC                 74.568607  AIC/n           0.0286142007
mean(Failure)      0.00306984  var(Failure)      0.00306041
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        2598     0.99693     0.99693    -7.407
State 1           8     0.00307     0.00307    -25.88
Total          2606     1.00000     1.00000    -33.28
```

Table 7 Four quarters lead time (variables with counterintuitive signs excluded based on the required level of statistical significance)

```
CS(83) Modelling Failure by Logit
       The estimation sample is 1 - 2598

                  Coefficient  Std.Error  t-value  t-prob
Constant            -0.574956      1.939   -0.297   0.767
DEP/L               -0.105454    0.02953    -3.57   0.000
MOR/L              -0.0650737    0.01470    -4.43   0.000
INTMARG               1.06586     0.3968     2.69   0.007
ISF/TA                7.20204      3.082     2.34   0.020

log-likelihood    -29.3623508  no. of states              2
no. of observations      2598  no. of parameters          5
baseline log-lik    -54.25212  Test: Chi^2(  4)       49.78 [0.0000]**
AIC                68.7247015  AIC/n             0.0264529259
mean(Failure)      0.00307929  var(Failure)        0.00306981
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        2590     0.99692     0.99692    -6.779
State 1           8     0.00308     0.00308    -22.58
Total          2598     1.00000     1.00000    -29.36
```

Table 8 Model 2 (one quarter lead time)

```
CS( 7) Modelling Failure by Logit
       The estimation sample is 1 - 2622

                  Coefficient  Std.Error  t-value  t-prob
Constant              12.3818      4.986     2.48   0.013
CAP                 -0.692375     0.3892    -1.78   0.075
ROA1                 -48.4282      15.42    -3.14   0.002
MOR/L              -0.0634681    0.01725    -3.68   0.000
LIQ                -0.0697293    0.04013    -1.74   0.082

log-likelihood    -25.8780026  no. of states              2
no. of observations      2622  no. of parameters          5
baseline log-lik    -54.32579  Test: Chi^2(  4)      56.896 [0.0000]**
AIC                61.7560051  AIC/n             0.0235530149
mean(Failure)      0.00305111  var(Failure)         0.0030418
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        2614     0.99695     0.99695    -7.352
State 1           8     0.00305     0.00305    -18.53
Total          2622     1.00000     1.00000    -25.88
```

Table 9 Model 3 (one quarter lead time)

```
CS( 8) Modelling Failure by Logit
       The estimation sample is 1 - 2622

                  Coefficient  Std.Error  t-value  t-prob
Constant             -20.6645      3.969    -5.21   0.000
L/E                  0.342407     0.1323     2.59   0.010
CIL/RA                7.85610      1.703     4.61   0.000
ISF/TA                3.99600      2.384     1.68   0.094
C/I                   8.37215      3.519     2.38   0.017

log-likelihood    -37.4259939  no. of states              2
no. of observations      2622  no. of parameters          5
baseline log-lik    -54.32579  Test: Chi^2(  4)        33.8 [0.0000]**
AIC                84.8519878  AIC/n             0.0323615514
mean(Failure)      0.00305111  var(Failure)         0.0030418
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        2614     0.99695     0.99695    -7.492
State 1           8     0.00305     0.00305    -29.93
Total          2622     1.00000     1.00000    -37.43
```

Table 10 Noise-to-signal-ratio and Type 1 and Type 2 errors at different thresholds

	Threshold:	**0.015**	**0.02**	**0.03**	**0.04**	**0.05**	**0.07**	**0.1**	**0.12**	**0.15**
Model 1	Type 1 errors	0	0	0	1	1	1	1	3	4
	Type 2 errors	6	5	4	3	3	3	3	2	2
Noise-to-signal-ratio		0.0469	0.0391	0.0313	0.0268	0.0268	0.0268	0.0268	0.0250	0.0313
Model 2	Type 1 errors	0	1	1	1	1	2	2	2	4
	Type 2 errors	7	7	6	6	4	4	2	1	1
Noise-to-signal-ratio		0.0547	0.0625	0.0536	0.0536	0.0357	0.0417	0.0208	0.0104	0.0156
Model 3	Type 1 errors	3	3	3	4	4	5	5	5	5
	Type 2 errors	10	7	5	4	2	1	1	1	1
Noise-to-signal-ratio		0.1250	0.0875	0.0625	0.0625	0.0313	0.0208	0.0208	0.0208	0.0208

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