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Leading indicators of distress in Danish banks in the period 2008-12

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SUMMARY: *Several Danish small and medium-sized banks have become distressed during and after the global financial crisis. In this paper, a multiple logistic regression model is used to identify which factors characterize the distressed Danish banks from 2008-12. The factors are chosen from a broad range of variables, i.e. the model is unrestricted. The estimated model identifies the distressed banks fairly well. The variables that altogether best describe the probability of a bank becoming distressed are: a bank's excess capital in per cent of risk weighted assets, the 3 year average lending growth lagged 2 years, property exposure, and a benchmark for stable funding (the so-called funding-ratio). The variables are all adjusted with the sector average to account for the general development during the period.*

Based on experiences from this and past crises the Danish FSA introduced the so-called »Supervisory Diamond« as part of its banking supervision in 2010. A multiple logistic regression model is estimated with deviations from limit values set in the supervisory diamond to assess whether the variables in the supervisory diamond differ from the unrestricted model. Overall, the analyses support the establishment of benchmarks. The results of this analysis show that deviations from the benchmarks concerning property exposure and funding-ratio are statistically significant with expected signs. However, deviations from the benchmarks concerning lending growth, large exposures, and excess liquidity cover are statistically insignificant.

1. Introduction and related literature

Internationally a number of banks and other financial institutions have become distressed during the global financial crisis. State interventions and costly bank bail-outs have been undertaken. After the crisis, new international regulation, not least in the

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form of stronger liquidity and capital requirements (Basel III and CRD IV), has been introduced in order to strengthen the resilience of the financial system. Focus has also been on promoting sound supervisory systems reflected in a review and update of the Basel »Core Principles for Effective Banking Supervision«, cf. Basel Committee on Banking Supervision (2012).

New national regulation has been introduced in several countries and reforms of supervisory practices have been undertaken. The Danish Financial Supervisory Authority (FSA) introduced the so-called »Supervisory Diamond« in 2010 as part of its banking supervision. The supervisory diamond consists of a number of benchmarks encompassing what must be considered as banking activity subject to enhanced risk, such as high lending growth, less stable funding conditions, etc. (the supervisory diamond is defined precisely in Section 5.1). These benchmarks are based on characteristics of the banks that became distressed during the crisis – characteristics also experienced in previous crises. Danish banks should keep to the limit values as of end 2012. The idea behind the supervisory diamond is that it should identify, and ultimately prevent, banks pursuing a more risky strategy at an early stage. In other words, it will help reduce risks in the banking system going forward.

In order to identify banks at risk early on, it is necessary to understand what the key drives were for banks that became distressed during the recent crisis. The scope of this paper is to analyse what characterized the distressed banks in Denmark during the period 2008-12 primarily by using information from the banks' financial statements. In Denmark, the distress of a bank was in most cases revealed during an examination performed by the FSA. Although the timing of these examinations is risk-based it is difficult to estimate the exact timing of a bank becoming distressed. As a consequence, the results of this model are interpreted as risk indicators of a bank becoming distressed in the nearby future rather than an exact timing of the distress event. In other words, this paper primarily identifies the leading indicators of distressed banks in the period around the global financial crisis and does not develop a model that as such predicts distress in banks. The paper is, however, related to the literature regarding early warning signals. A wide range of central banks and/or supervisory authorities have developed models to identify problem banks and refer to these in their Financial Stability reports, e.g. Deutsche Bundesbank, cf. Porath (2004), European Central Bank, cf. Betz et al. (forthcoming), Norges Bank, cf. Andersen (2008), Oesterreichische Nationalbank, cf. Hayden et al. (2004), Bank of England, cf. Logan (2001) and in the USA the Office of the Comptroller of the Currency, cf. Whalen (2010) and Federal Reserve, cf. Thomson (1991), Whalen (1991) and Jagtiani et al. (2003). The models consist of both logit models and hazard rate models. In Hayden et al. (2004) both types of models are estimated and complement each other.

During the period 2008-12, 26 Danish banks became distressed[1] comprising 6 per cent of the total assets of Danish banks[2] by end 2007. In order to model distressed banks, a multiple logit model is estimated using lagged explanatory variables such as lending growth, amount of capital in the banks, exposure to the real estate market, etc.[3] The variables that are included in the finally chosen unrestricted model are excess capital (capital in excess of the solvency requirement of the individual bank) in per cent of risk weighted assets, the 3 year average lending growth lagged 2 years, property exposure, and the funding-ratio (a measure of the liquidity position of banks).

These results, based on the present crisis, are overall in line with the experience from the previous banking crisis in Denmark during the late 1980s to early 1990s. In general the banks that became distressed during the previous crisis had a higher occurrence of rapid lending growth prior to the crisis, a higher lending to capital ratio, lower excess capital, lower and decreasing return on capital, and a higher concentration of large exposures than the non-distressed banks, cf. the Ministry of Economic Affairs (1995). One important difference between the crises in 1987-93 and 2008-09 is that the liquidity position of the banks has been a significant factor during this crisis but not during the previous crisis. This difference is due to the shift in the bank funding structure round about the millennium rollover. The funding structure switched from lending and deposits being more or less balanced to a customer funding gap financed by issuing short-term bonds and borrowing from foreign credit institutes, cf. Abildgren et al. (2011).

The supervisory diamond consists of a number of benchmarks encompassing what must be considered as banking activity subject to enhanced risk. This paper also examines whether the variables in the supervisory diamond differ from the unrestricted model.[4] Due to their distinct purposes differences between the two approaches should be expected. The ultimate purpose of the supervisory diamond is to prevent banks from pursuing a risky strategy, i.e. when banks know the limits of the supervisory diamond, they will adhere to these limits going forward. On the other hand, the purpose of the unrestricted model is to identify the characteristics of the banks that have become distressed in the period 2008-12.

1. In this paper a distressed bank encompasses not only failed banks but also mergers in distress. The definition of distressed banks is described in Section 3.1.

2. Danish banks comprise the Danish Financial Supervisory Authority's groups 1, 2 and 3.

3. In the related literature a number of different variables are found significant when predicting banks becoming distressed, in particular lending growth, property exposure, earnings, capital, etc., cf. Whalen (1991), Thomson (1991), Logan (2001) and Andersen (2008). Demirgüc-Kunt (1989) and Kumar et al. (2007) provide overviews of related studies.

4. Given that the model analyzing the supervisory diamond prespecifies certain variables, and thereby restricts the analysis to these variables, we call this the »restricted« model in the remaining part of the paper. Likely, the model based upon examining all potential variables is called the »unrestricted« model.

Two differences are identified. First, last year's lending growth enters into the supervisory diamond whereas in the univariate regressions lending growth over one year is not statistically significant in relation to banks becoming distressed – only lagged high lending growth over several years is. However, the supervisory diamond sets a limit for yearly lending growth and thus puts limits on a higher yearly lending growth persisting over several years. Second, excess capital enters into the unrestricted model. The supervisory diamond does not include a role for the capital position of banks.

Two cautionary remarks regarding the results should be made. First, the supervisory diamond reflects the experiences from both the current crisis and the crisis in the early 1990s. For this reason, it is not surprising that different results are found when estimating an unrestricted model versus a model based on the supervisory diamond. Second, and related, it would be interesting to estimate a model including data from both crises. However, due to data limitations this is not straightforward, and is beyond the scope of this paper.

Before commencing the paper itself, we note that we are not the first to study determinants of risk taking in the Danish banking sector during the years surrounding the recent financial crisis, see for instance Bechmann and Raaballe (2009, 2011), Rose (2010), and Østrup (2013). These authors primarily study corporate governance characteristics as possible explanations for differences in risk taking across banks. Bechmann and Raaballe (2009, 2011) find that restrictions on voting rights as well as other shareholder restrictions contributed to higher risk taking in banks with such restrictions, as they allowed CEOs to take on too much risk without being »stopped« by independent boards and owners. Rose (2010) and Østrup (2013) question the conclusions of Bechmann and Raaballe. These papers generally measure risk taking by variables such as lending growth, deposit deficit etc. Finally, Bechmann and Raaballe (2009, 2011) and Rose (2010) study a subsample of the Danish banking sector (listed banks). We differ from these papers by studying a larger sample of banks (and explanatory variables), focusing on bank failures themselves instead of implicit measures of risk taking (such as lending growth) and on observable »hard-core« economic and financial variables (and less on corporate governance issues), which relates our paper more directly to the international literature mentioned above. Finally, we study potential effects of the Supervisory Diamond. In addition to these papers, in the report on the financial crisis in Denmark, cf. Rangvid et al. (2013), there are general and more elaborate descrip-primarilytions of why Danish banks failed, but no formal statistical analyses.

After these introductory remarks the rest of the paper proceeds as follows. In Section 2 the econometric method is discussed and described. In Section 3 the data are described followed by estimations of unrestricted logit models resulting in a final unrestricted model in Section 4. In Section 5 logit models with the benchmarks in the supervisory diamond are estimated. Section 6 concludes and offers scope for further research.

2. Econometric method

In the related literature different models, especially hazard models and logit/probit models, are used as indicators of the soundness of banks, see Kumar et al. (2007) for a review of applied methods. The aim of the models is typically to identify problem banks in advance in order to be able to take action to reduce the likelihood of bankruptcies, i.e. early warning signals.

Logit and hazard models have both strengths and weaknesses. For instance, Shumway (2001) and Cole (2009) argue that a hazard rate model is preferred to a logit model primarily because there is no conflict with the assumption of independent observations in the hazard model. An example of a hazard rate model is in Halling (2007). However, in hazard models the time to failure is estimated. The weakness of these models, therefore, is that it is assumed that all banks will fail eventually (survival theory), cf. Cole et al. (1995). This is not assumed in logit models. On the other hand, the logistic model assumes that the observations are independent. This is a strong assumption since the data contains multiple observations from the same bank at different points in time.

In this paper we follow Andersen (2008), Thomson (1991), Logan (2001), and Poghosyan et al. (2009) and use a multiple logistic regression model. The logit models are typically estimated using annual data, with the explanatory variables being lagged 1 or 2 years. As an example of such a logit model, Whalen (1991) sets up a model using year-end 1986 data and estimates the probability of failure within the succesive 0-24 months.

The models estimated in this paper assume a linear relationship between the explanatory variables and the response variable. This might not capture all dimensions of the data and in several studies the variables are transformed to ensure the linear relationship, cf. Porath (2004). The linear relationship is proxied by adjusting the variables with the sector average and thus takes into account the general development in the period. In addition,[5] when using variables adjusted for sector developments, it will be easier to compare the results from such models with those from a model based on the supervisory diamond that adjusts for limits on certain benchmark variables, cf. Section 5.

3. Data

The explanatory variables in related literature are either market-based or derived from banks' financial statements or a combination of both. In several studies these variables are combined with macro variables. The advantage of using market-based vari-

5. The sector is defined as the banks in the Danish Financial Supervisory Authority’s groups 1, 2 and 3.

Table 1. Number of banks and number of distressed banks.

Year-end	Banks	Of which number of distressed banks issuing last annual report	Relative frequency, per cent	Number of banks and the year of distress announcement
2006	92	1	1.1	
2007	95	9	9.5	
2008	86	2	2.3	9
2009	84	7	8.3	3
2010	78	4	5.1	4
2011	77	3	3.9	5
2012	–	–	–	5
Total	512	26	5.1	26

ables rather than accounting figures is that the first are based on expectations to future earnings, i.e. are forward-looking, whereas the latter are backward-looking.

The aim of this study is to analyse distresses in all Danish banks. However, many of these are not listed. For this reason, the explanatory variables used here are primarily from the financial statements supplemented with macro variables to account for business cycle variations (i.e. change in GDP, property prices, interest rate and unemployment rate). It is important to notice that variables derived from the financial statements can only indicate beginning problems if the financial statements give an accurate picture of the health status of the institutes, as already noted in the Ministry of Economic Affairs (1995).

The model comprises data from Danish banks included in the Danish Financial Supervisory Authority's groups 1, 2 and 3. They comprise banks with working capital (deposits, bonds issued etc., subordinated capital and equity capital) of at least approximately EUR 33.5 million. Some niche banks are excluded.[6] Some of the banks are parent companies to other financial enterprises and prepare both separate and consolidated financial statements. To analyse the banking activities of the institutions the analysis is therefore based on the separate financial statements, i.e. unconsolidated data.

In Table 1 the number of banks having presented financial statements for the year in question and the number of distressed banks are listed. For instance 9 banks were distressed whose last financial statement was for the year 2007.[7] In total there are 512 observations.

6. These are: FIH Kapitalbank and Ekspres Bank have no deposits, Bank DNB Nord and SEB Bank are Norwegian and Swedish subsidiaries respectively, and they have returned their Danish banking licenses in 2012 and merged with their respective parent companies. Saxo Bank (bought E-trade Bank in 2009) and Carnegie Bank are primarily investment banks.

A final remark regards the registration of distress in the data. The distress of a bank is attributed to the last financial statement reported from a distressed bank. There can be a considerable time lag from the publication of the last financial statement of a distressed bank until the date of the announcement of the distress. For instance, in Table 1 the distressed bank that returned its last financial statement for the year 2006 was announced distressed in early 2008. This is in line with the results of the models that are interpreted as risk indicators of a bank becoming distressed in the nearby future rather than an exact timing of the distress event.

3.1. Identification of distressed banks

From 2008 until March 2013 60 banks in Denmark have ceased business. This number comprises 19 smaller ceased banks not included in the model, i.e. the Danish FSA's group 4 banks with a working capital of less than approximately EUR 33.5 million. Neither ceases of foreign nor niche banks are included in the analysis, cf. footnote 5; 4 such banks have ceased business during the period. One bank ceased business in 2013 and is not included in the model.[8] 11 of the banks have been taken over by Finansiel Stabilitet A/S[9] – the government-owned company in charge of the resolution of distressed banks – and are identified as distressed. Of the remaining ceased banks it is assessed whether the banks had a viable business model in the short run. If not, the bank is identified as distressed. Ultimately 26 ceased banks are identified as distressed during the period, cf. Table 1 and Appendix 1.

3.2. Explanatory variables

Data are from the individual banks' quarterly financial statements reported to the Danish FSA.[10] Approximately 55 variables have been selected and calculated. As in related literature the explanatory variables are grouped into different CAMELS categories to ensure that all key factors initially are encompassed in the model, cf. Appendix 2. CAMELS rating system is the United States' FSA's method of assessing the overall soundness of banks and stands for *C*apital adequacy, *A*sset quality, *M*anagement, *E*arnings, *L*iquidity and *S*ensitivity to market risk. The hypothesis is that these factors are key elements in assessing the health of a bank.

However, it is not possible to directly assess management competence through a financial statement. Instead some variables assessed to indicate management competence

7. Financial statements of solvent banks are included.
8. The takeover of Sparekassen Lolland by Jyske Bank announced on the 25th of January 2013 as a private solution on market conditions is not included as a distress event in the data.
9. Finansiel Stabilitet is a public limited company owned by the Danish State through the Ministry of Business and Growth, cf. www.finansielstabilitet.dk.
10. With the exception of lagged lending growth. It is calculated from statistics concerning »Balance sheets and flows of the MFI sector« as from 2003.

are derived from the statements, i.e. costs in per cent of earnings, cf. Appendix 2. One variable, interest rate risk, is included regarding sensitivity to market risk.

In the estimations the sector average has been subtracted from the variables (lending growth of bank i minus average lending growth of the sector) to take into account the general development in the period resulting in negative values for the banks below the sector average. To calculate yearly lending growth, the average equity during the year, etc., it is necessary to have financial statements from each bank for at least 5 succeeding quarters, otherwise the observation is not included.

If a bank is owned by another financial corporation there is a risk of negative reputation for the parent if the subsidiary becomes distressed. This implies that the bank might have a smaller probability of distress since the parent has an incentive to inject capital into its subsidiary in case of financial distress. Relevant information concerning owner structure has been collected from Greens online. A dummy variable is created: if a financial company owns more than 50 per cent of a bank it is regarded as having reputational risk and the dummy equals 1 and 0 otherwise. For 9 banks in the sample the dummy equals 1.[11]

On 3 February 2009 a bill on government capital injections into credit institutes was passed by the Folketing (Danish parliament). A dummy variable is included in the analysis equal to 1 if a bank received a capital injection from the government and 0 otherwise.

Furthermore four macroeconomic variables are included in the analysis, cf. the introduction of Section 3.

3.3. Descriptive statistics

In Appendix 2 the distribution of the median values of the explanatory variables is given by all banks, the non-distressed banks and the distressed banks respectively. Furthermore the expected signs of the coefficient estimates are given. Note that financial statements of the distressed banks prior to the last financial statement are registered as financial statements from non-distressed banks.

A priori, one would expect that the likelihood of a bank becoming distressed is lower the higher the level of capital in the bank. For this reason, Appendix 2 indicates that a negative sign is expected in the regressions. The Appendix also shows that the median of the distressed banks in general had lower levels of capital than the median of the non-distressed banks, and a higher leverage ratio.

The asset quality is expected to be lower in distressed banks and is captured by different indicators, for instance different measures of lending growth, property exposure, large exposures, loan impairment charges, concentration index, etc. In general the median distressed bank has a lower asset quality than the non-distressed banks.

11. The banks are: Alm. Brand Bank, BRF Bank, Lægernes Pensions Bank, Nordea Bank Danmark, Nykredit Bank, Nørresundby Bank, Pen-Sam Bank, Saxo Privatbank and Banque Internationale à Luxembourg Danmark.

Indicators of management competence such as cost in per cent of earnings, growth of deposits, the implicit margin between deposit and lending rates are expected to reduce the probability of distress. However, the statistics do not in all cases show a large difference between the distressed and non-distressed banks.

There might be a risk of endogenous and/or omitted variable bias problems concerning the implicit interest margin. For instance a bank that expects to face problems might raise the interest margin. This could induce clients to switch bank which will further enhance the need for the bank to increase the margin. Ultimately, this could potentially result in actual distress. In such a case the distress could be attributed to the rise in interest margin even when it was in fact other factors that initially triggered the distress event. In the data used here, this hypothesis, however, is not supported. The distressed banks both raised and lowered their margins in the year prior to distress.

As would be expected the variables measuring earnings clearly indicate lower earnings in distressed banks.

Liquidity issues might arise either due to funding liquidity (the ability to make payments when needed) or market liquidity (how quickly an asset can be liquidated without significant price effects) and are closely linked. In this analysis liquidity is proxied by the funding-ratio, excess liquidity cover and customer funding gap. Funding-ratio is defined as loans relative to working capital less bond issuance with a remaining maturity less than 1 year.[12] The different measures indicate a slightly lower level of liquidity in distressed banks than in other banks.

We assess that the majority of the Danish banks are subject to a fairly low level of market risk – credit risk is the dominant risk. Of the different market risks the interest rate risk constitutes a major part of the banking institutes' market risk. Therefore, sensitivity to market risk encompasses only one variable, the Danish FSA's key ratio »interest-rate risk«.[13] The statistics show a lower level of interest rate risk for the median of the distressed banks compared to the non-distressed banks.

4. Model

A logistic regression model is estimated where the probability of distress within the coming period t for bank i is given by:

$$P_{i,t} = \frac{exp(\alpha + \beta_j x_{i,t\text{-}1,j} + e_{i,t})}{1 + exp(\alpha + \beta_j x_{i,t\text{-}1,j} + e_{i,t})} \Leftrightarrow ln\left(\frac{P_{i,t}}{1 - P_{i,t}}\right) = \alpha + \beta_j x_{i,t\text{-}1,j} + e_{i,t}$$

where x is a vector of j explanatory variables measured in a previous period, α is a constant, β is the coefficient estimates, and e is the error term, cf. Allison (2012). Some of

12. Amount of loans and deposits is calculated excluding repo transactions.
13. The ratio is an expression of the part of the core capital (after deductions) which is lost on a parallel shift of the yield curve by 1 percentage point.

the explanatory variables are highly correlated meaning that a model including all the explanatory variables could suffer from co-linearity problems resulting in unreliable coefficient estimates. In particular variables measuring capital adequacy, asset quality and earnings are highly intercorrelated.

Due to the high correlation in the data, a selection process is developed to select the variables to be included in the final model. This selection process commences with a univariate regression for each explanatory variable. These regressions are performed both with the bank specific variable and the bank specific variable adjusted with the sector average. We then use different selection criteria to choose among the explanatory variables. In order to save space, we refer to Buchholst and Rangvid (2013) for a detailed description of these preliminary tests.

4.1. Results

The model we end up using comprises the following variables: excess capital in per cent of risk weighted assets, the 3 year average lending growth lagged 2 years, property exposure and funding-ratio. The results from estimating this model are given in Table 2.

The negative sign of the coefficient to excess capital means that the more excess capital the bank has the smaller the probability of distress. This is of course intuitive since higher excess capital ceteris paribus means greater stamina. In the same way higher lending growth, funding-ratio and property exposure entail higher probability of distress. It is important to point out, as mentioned, that the included variables are adjusted with the average of the sector. This means that the probability of distress is higher if, for instance, the property exposure for a given bank is higher than the average of the sector and vice versa.

Lending growth is in general statistically significant. However, out of the different variables for lending growth the one that is statistically most significant is the 3 year average lending growth lagged 2 years.[14] This means that approximately 2 years pass before an extensive lending growth over 3 years affects the financial statement of the bank to such a degree that the probability of distress increases. In the results from our model selection procedure, cf. Buchholst and Rangvid (2013), we show that high lending growth in a single year does not have a statistically significant effect on the probability of distress the following year. On the other hand, if the bank has a high lending growth that continues for several years it increases the probability of distress significantly, cf. Table 2.

Other indicators of asset quality are also highly statistically significant in the univariate regressions, such as large exposures and loan impairment charges. Due to the

14. Data on lending goes back to 2003 meaning that the variable until 2008 contains average yearly lending growth to date lagged 2 years.

Table 2. Coefficient estimates, unrestricted model.

Variable	Coefficient estimate (standard error) *p*-value	Odds ratio
Constant term	-3.5228*** (0.3028) <0.0001	0.029
Excess capital, per cent of RWA	-0.1486** (0.0668) 0.0262	0.862
3 year average lending growth lagged 2 years	0.0513*** (0.0182) 0.0049	1.053
Property exposure	0.0351** (0.0142) 0.0134	1.036
Funding-ratio	0.6669** (0.3260) 0.0408	1.948
Pseudo-R^2	0.1959	
AUC	0.820	

Note: Standard error in parenthesis. *** indicates that the variable is statistically significantly different from 0 at a 1 per cent level of significance, ** indicates that the variable is statistically significantly different from 0 at a 5 per cent level of significance and * indicates that the variable is statistically significantly different from 0 at a 10 per cent level of significance. A *p*-value less than 0.05 rejects the null hypothesis. Odds ratio equals OR = e^{β}. AUC measures the size of the Area Under the receiver operating Curve. The Receiver Operating Curve (ROC) shows the sensitivity (estimated distress relative to actual distress) and 1 minus specificity (estimated non-distress relative to actual non-distress). The higher and more to the left the curve is located, the better fit of the model. A model that fits the data perfectly has an AUC equal to 1 and will reach the upper left corner whereas a random model will have an AUC equal to 0.5. Pseudo-R^2 equals SAS® output max re-scaled *R*-square.

highly correlated nature of these variables, they are not included in the final model. The same explanation applies for the variables measuring earnings. The different variables indicating management competence are statistically insignificant.

It is difficult to quantify the effect of a change in the variables on the probability of distress from the coefficient estimate. Instead the odds ratio is applied. It measures the probability of distress relative to the probability of non-distress, cf. Table 2. This relative distress risk is simply referred to as the probability of distress in the following.

The percentage change in the probability of distress by a 1 unit change in a variable is found by subtracting 1 from the odds ratio for a quantitative variable. For instance an increase of 1 percentage point in the excess capital in per cent of risk weighted assets adjusted with the sector average reduces the probability of distress by 14 per cent.

Since the explanatory variables are adjusted with the sector average the probability of distress for the average bank will equal the constant term of around 3 per cent, cf. Figure 1.[15]

The banks with the estimated highest probabilities of distress show a rising tendency of their probability of distress until 2010 which presumably is due to the high lending growth which took place from 2005 till 2008. The impact of the high lending growth on the probability of distress peaks in 2010 because the average lending growth is lagged 2 years, cf. Figur 1.

Average lending growth in the Danish banking system was high before the crisis. As mentioned the variables in this analysis are included as »deviation from means«, i.e. sector averages have been subtracted from the individual variables. One could be concerned that we do not capture the overall level of risk taking in the banking sector (in the form of for instance high overall lending growth) by using deviations from sector averages. In order to make sure that this choice of model design does not affect the results for the average bank, a model including the sector's average 3 year lending growth lagged 2 years was also estimated. This robustness check therefore controls for overall lending growth in the economy. The result of this model was a slightly bell-shaped curve for the probability of distress for the median bank, cf. Appendix 3. The coefficient estimate for this extra included variable (sector's average 3 year lending growth lagged 2 years) was statistically insignificant and the fractiles nearly the same. However, the median probability of distress is increased from slightly below 3 per cent to around 4 per cent in 2010.

Finally, it should be mentioned that none of the macrovariables are significant. One reason for this could be that the timing of a distress sometimes occurs with a time lag, as mentioned and discussed in Section 3.[16]

4.2. Model validation

In the following sections the performance of the model is examined in two different ways. First, the classification accuracy of the model is analysed, i.e. how precise is the model at discriminating between the distressed and non-distressed banks. And second, how effective is the model in discriminating between distressed and non-distressed banks on out of sample data.

15.
$$P_{i,t} = \frac{exp(-3.5228)}{1 + exp(-3.5228)} = 0.029$$

16. Time lags are also realized because defaults sometimes occur as a result of an inspection by the FSA. For some banks, such inspections occur with intervals spanning several years.

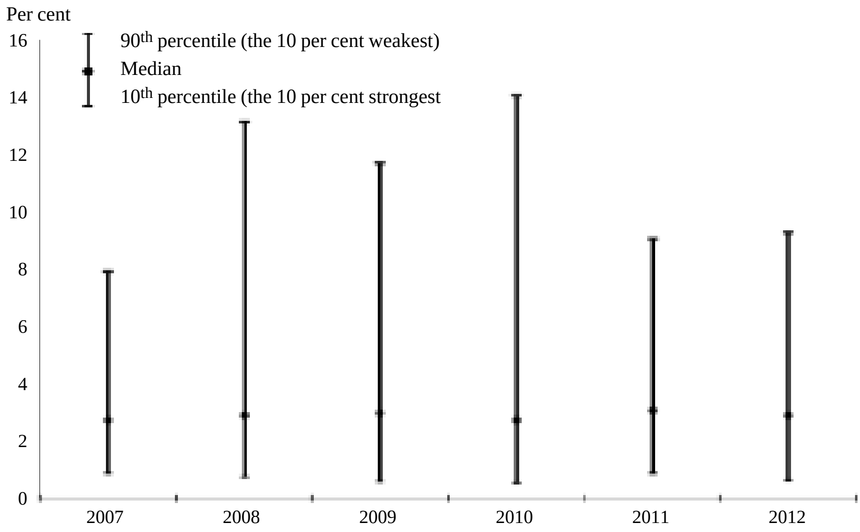

Figure 1. Estimated probability of distress, unrestricted model.

Note: The probability of distress at year-end.
Source: Own calculations.

4.2.1. Accuracy of the model

The classification table in Table 3 shows, at a chosen threshold, how many observations the model classifies correctly.

A threshold of 1.3 per cent means that banks with an estimated probability of distress higher than 1.3 per cent will be classified as distressed, cf. Table 3. At this threshold 24 actually distressed banks will be classified as distressed, but 373 observations that are non-distressed will also be classified as distressed (i.e. false alarms). The threshold is therefore set higher, at 7 per cent, which is also closer to the relative frequency of distressed banks compared with non-distressed banks, cf. Table 1. As can be seen from Table 3, 17 actually distressed banks will be classified as distressed and 73 observations that are non-distressed will be classified as distressed. It is also seen that 9 distressed banks had an estimated probability of distress below 7 per cent which will not be identified by the model as distressed at this threshold. Finally it is seen that there are 2 distressed banks where the estimated probability of distress is below 1 per cent. The model does not capture the distress of these banks at all.

In the related literature the threshold indicates the preference of the supervisor between missing distress events versus false alarms. If a supervisory examination can detect problems early enough, regulatory actions can be taken either to prevent a bank from failing or to minimize the cost of a failure, arguing in favour of a relatively low threshold, cf. Thomson (1991). However, the aim of this analysis is to identify the fac-

Table 3. Classification table.

	Correct classification		Incorrect classification		Percentages				
Probability level	Distress	Non-distress	Distress (of wich no distress in later period), of which unique banks	Non-distress	Correct classification	Sensitivity	Specificity	Incorrectly classified distresses	Incorrectly classified distresses
0.01	24	73	413 (351) 73	2	18.9	92.3	15.0	94.5	2.7
0.013	24	113	373 (312) 69	2	26.8	92.3	23.3	94.0	1.7
0.02	24	177	309 (255) 64	2	39.3	92.3	36.4	92.8	1.1
0.03	23	263	223 (176) 50	3	55.9	88.5	54.1	90.7	1.1
0.04	21	318	168 (125) 41	5	66.2	80.8	65.4	88.9	1.5
0.05	20	362	124 (86) 33	6	74.6	76.9	74.5	86.1	1.6
0.06	18	394	92 (60) 25	8	80.5	69.2	81.1	83.6	2.0

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	Correct classification		Incorrect classification			Percentages			
Probability level	Distress	Non-distress	Distress (of wich no distress in later period), of which unique banks	Non-distress	Correct classification	Sensitivity	Specificity	Incorrectly classified distresses	Incorrectly classified distresses
0.07	**17**	**413**	**73** **(43)** **19**	**9**	**84.0**	**65.4**	**85.0**	**81.1**	**2.1**
0.08	16	425	61 (34) 16	10	86.1	61.5	87.4	79.2	2.3
0.10	11	444	42 (20) 10	15	88.9	42.3	91.4	79.2	3.3

Note: Cross validated probabilities. Sensitivity equals estimated distress relative to actual distress. Specificity equals estimated non-distress relative to actual non-distress. Each cell in the fourth column consists of three figures: the first figure is the number of incorrectly classified distress observations (in the first cell: 413), the second figure shows how many of these falsely classified distress observations that are not distressed in later periods (in the first cell: 351), and finally the third figure shows how many unique banks that are falsely classified as distressed that are not distressed in a later period (in the first cell: 73).

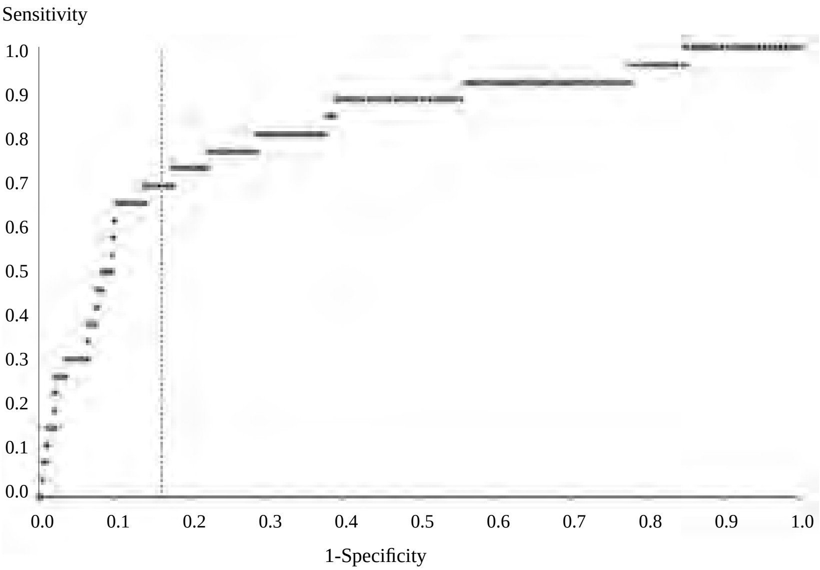

Figure 2. ROC curve, unrestricted model.

Note: The dotted line shows the threshold level of 7 per cent.

tors characterizing the distressed banks in the period and the threshold is chosen also to account for an acceptable level of false alarms.

The 73 incorrectly classified distresses comprise 30 observations that became distressed in one of the following years until 2012 (13 different banks) reducing the number of incorrect classifications to 43, of which some banks appear in several periods which means that ultimately 19 different banks are incorrectly classified as distressed, cf. Table 3.

Classification tables can be illustrated graphically by the Receiver Operating Characteristic curve (ROC). The curve shows the sensitivity (estimated distress relative to actual distress) and 1 minus specificity (estimated non-distress relative to actual non-distress), cf. Figure 2. The higher and more to the left the ROC curve is located, the better fit of the model. A model that fits the data perfectly has an AUC equal to 1 and will reach the upper left corner whereas a random model will have an AUC equal to 0.5. The AUC in this model is 0.82. At a threshold level of 7 per cent 65 per cent of the distressed banks are classified correctly and 84 per cent of the non-distressed banks respectively.

4.3. Model validation: Predicted distress in 2012

The robustness of the model is examined by reestimating the model for a subset of

Table 4. Cofficient estimates, model up to and including 2010 financial statements.

Variable		Coefficient estimate (standard error) *p*-value	Odds ratio
Constant term		-3.5186***	
		(0.3295)	
		<.0001	0.029
Excess capital, per cent of RWA		-0.1594**	
		(0.0732)	
		0.0295	0.853
3 year average lending growth lagged 2 years		0.0438**	
		(0.0193)	
		0.0230	1.045
Property exposure		0.0400***	
		(0.0154)	
		0.0093	1.041
Funding-ratio		0.7185**	
		(0.3588)	
		0.0452	2.051
Pseudo-R^2	0.2116		
AUC	0.834		

Note: Standard error in parenthesis. *** indicates that the variable is statistically significantly different from 0 at a 1 per cent level of significance, ** indicates that the variable is statistically significantly different from 0 at a 5 per cent level of significance and * indicates that the variable is statistically significantly different from 0 at a 10 per cent level of significance. A *p*-value less than 0.05 rejects the null hypothesis. Odds ratio equals OR = e^{β}. See note to Table 2 for a definition of AUC. Pseudo-R^2 equals SAS® output max re-scaled *R*-square.

the data and testing this model on the remaining data. The model is estimated on the same data excluding the observations from year-end 2011 corresponding to 435 observations of which 23 distresses, compared to the full sample which comprised 512 observations of which 26 distresses.

The variables are all statistically significant, the signs correspond to the ones found in the model estimated on the full sample and the coefficient estimates are within the confidence intervals found in the full sample estimation, cf. Table 4.

The out of sample data consists of financial statements for 2011 for 77 banks of which 3 were distresses. The calculated probabilities of distress show that 11 banks have an estimated probability of distress higher than 7 per cent (10 banks in the model estimated on the full sample), however, only 1 of the 3 actual distressed banks is among them. On the other hand the model does not capture the distress of the 2 other distressed banks as was the case in the model estimated on the full sample, cf. Table 5.

Table 5. Estimated probabilities of distress in 2012.

Bank	Full sample estimated probability	Out of sample estimated probability
Distressed bank 1	0.20	0.21
Distressed bank 2	0.05	0.05
Distressed bank 3	0.02	0.02

The model is thus fairly robust in estimating probabilities of distress also for data not included in the model.

5. Model including Supervisory Diamond variables

5.1. Background

After the financial crisis there has been an increased focus both nationally and internationally on supervisory practices. The Basel »Core Principles for Effective Banking Supervision« have been updated and reviewed to take into account *»significant developments in the global financial markets and regulatory landscape since October 2006, including post-crisis lessons…«*, cf. Basel Committee on Banking Supervision (2012).

New national regulation and reforms of supervisory practices have also been introduced in several countries. In the UK, for instance, the intention of creating three new regulatory bodies was announced in June 2010. Similarly, in the context of the European Union, a new supervisory framework is being developed as part of a broader vision of a European banking union.

The Danish FSA introduced the so-called »Supervisory Diamond« as part of its banking supervision in 2010.[17] The supervisory diamond consists of a number of benchmarks encompassing what must be considered as banking activity subject to enhanced risk. Danish banks are required to comply with the limit values as of end 2012. The benchmarks of the supervisory diamond concern lending growth, property exposure, large exposures, funding-ratio, and excess liquidity cover. The limit values are as follows:

– Sum of large exposures (less than 125 per cent of total capital)
– Lending growth (less than 20 per cent per year)
– Commercial property exposure (less than 25 per cent of total loans)
– Funding-ratio (lending/working capital – less bond issuance with remaining maturity less than 1 year). Limit value: less than 1
– Excess liquidity cover (over 50 per cent)

17. Letter from The Danish Financial Supervisory Authority of June 25th 2010 and letter of December 14th 2010, cf. *www.ftnet.dk*.

Table 6. Correlation matrix, deviation from limit values.

	Lending growth	Large exposures	Funding-ratio	Property exposure	Excess liquidity cover
Lending growth	**1.0**				
Large exposures	0.14	**1.0**			
Funding-ratio	0.15	**0.46**	**1.0**		
Property exposure	-0.04	**0.42**	0.19	**1.0**	
Excess liquidity cover	**-0.31**	-0.23	**-0.42**	-0.03	**1.0**

Note: Figures in bold represent a correlation greater than 0.3.

5.2. Model and explanatory variables

As in the previous section a multiple logistic regression model is estimated where the probability of distress for each bank is estimated. The explanatory variables comprise a constant term as well as the values of the five benchmarks adjusted with the limit values set in the supervisory diamond.[18]

The limit value for excess liquidity cover is a minimum requirement while the limits for the other benchmarks are maximum requirements. The maximum requirements are met if the variable is negative and vice versa for the excess liquidity cover. A positive sign for one of the coefficients of the maximum requirements entails ceteris paribus that the probability of distress is reduced if the limit is met and similarly for a negative estimate for the excess liquidity cover.

The benchmarks are to some extent correlated, cf. Table 6. For instance property exposure is correlated with large exposures. However, the correlation is not perfect and not nearly as high as in the previous section, and a model is estimated including all five benchmarks adjusted with the limit values.

5.3. Results

We will in this section describe the results from the model where we include the values of the benchmark variables adjusted by the limit in the Supervisory Diamond, and we will compare these results with those we found in the previous section. Before doing so, it is important to notice that even when the variables entering both models are deviations from a number, there is a fundamental difference between the two models: When we adjust a variable with a sector average, as in Section 4, this is a dynamic adjustment, as the sector average obviously differs from year to year, whereas when we

18. Due to changes in definitions and lack of data it is not possible to calculate the exact benchmarks back in time. For instance the definition of large exposures has changed and data on term to maturity on debt instruments is not available. All debt instruments are presumed to have a term to maturity over 1 year.

Table 7. Supervisory diamond, full sample, estimation process.

Variable	Step 1	Step 2	Step 3	Step 4
Constant term	-2.1267***	-2.1311***	-2.0907***	-2.4979***
	(0.3187)	(0.3171)	(0.3085)	(0.2177)
	<0.0001	<.0001	<0.0001	<0.0001
Lending growth	-0.00352			
	(0.00956)			
	0.7129			
Large exposures	0.00165	0.00152		
	(0.00264)	(0.00263)		
	0.5312	0.5626		
Funding-ratio	0.518	0.5331	0.6492***	0.8418***
	(0.3751)	(0.3725)	(0.3145)	(0.3224)
	0.1673	0.1523	0.039	0.009
Property exposure	0.0432***	0.0439***	0.048***	0.0404***
	(0.0148)	(0.0147)	(0.0128)	(0.0116)
	0.0035	0.0027	0.0002	0.0005
Excess liquidity cover	-0.004	-0.00366	-0.00394	
	(0.00266)	(0.00246)	(0.00244)	
	0.1328	0.1369	0.1057	
Pseudo-R^2	0.1234	0.1226	0.1208	0.1034
AUC	0.778	0.773	0.769	0.788

Note: Standard error in parenthesis. *** indicates that the variable is statistically significantly different from 0 at a 1 per cent level of significance, ** indicates that the variable is statistically significantly different from 0 at a 5 per cent level of significance and * indicates that the variable is statistically significantly different from 0 at a 10 per cent level of significance. A *p*-value less than 0.05 rejects the null hypothesis. See note to Table 2 for a description of AUC. Pseudo-R^2 equals SAS® output max re-scaled *R*-square.

adjust the benchmark variables specified by the supervisory diamond with its limits, these limits are time-invariant, as explained in Section 5.2.

Property exposure and funding-ratio are both highly statistically significant with positive signs, cf. Table 7. The larger the deviation from the limit values set in the supervisory diamond the higher probability of distress. The three other benchmarks are not statistically significant. The statistical insignificance of lending growth can reflect that effects of a, perhaps, not so strict lending policy take a few years to materialize in the financial statements.

The estimated probabilities for the median bank are slightly higher than in the previous model and lower for the 10 per cent with the highest probabilities, cf. Figures 1 and 3. If a bank exactly meets the limit values in the supervisory diamond the probability of distress is given by the constant term, equal to 7.6 per cent and it would actually

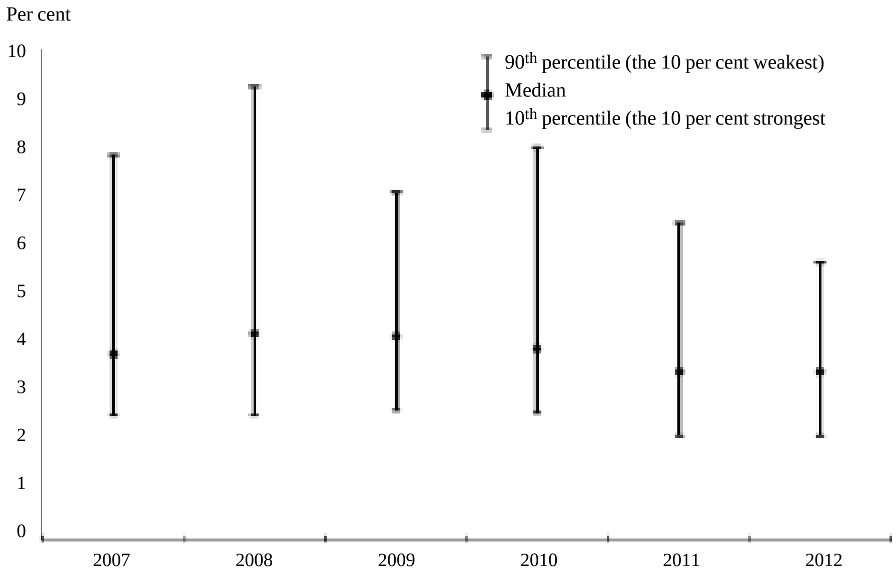

Figure 3. Estimated probabilities of distress, supervisory diamond.

Note: Model with a constant term, property exposure and funding-ratio adjusted with limit values.
Source: Own calculations.

be classified as distressed. The differences between the results from the unrestricted model (Table 2 and Figure 1) and the model based on the supervisory diamond (Table 7 and Figure 3) relate to the different specifications and objectives of the models. The main difference is that – in the unrestricted model analysed in Section 4 – the variables were adjusted with the sector averages to take into account the general development whereas – in the model in this section – the adjustments are given by the limit values in the supervisory diamond and are fixed. Second, a wider range of variables are included in the previous model and the specification is unrestricted whereas the model including the benchmarks from the supervisory diamond is restricted to these variables. These differences result in a lower explanatory power in this model than in the model in the previous section, measured by pseudo R-squared and AUC.Finally, it should be noted that the banks were not required to comply with the benchmarks set in the supervisory diamond before end 2012 and the purpose of these benchmarks is to ultimately prevent excessive risk taking. Thus, since Danish banks from end 2012 are required to comply with the supervisory diamond, it seems reasonable to assume that the variables eventually will become statistically insignificant. Such an outcome will, however, depend on whether the banks in the end will fulfill the limits defined in the supervisory diamond.

5.4. Model validation: Classification table

If the threshold for the probability level is set at 7 per cent as in the previous section the model will identify half of the distressed banks and 55 non-distresses will be identified as distressed, cf. Appendix 4. In comparison, the model in the previous section identified more distresses, however, also more false alarms. The AUC equals 0.788 indicating that the model explains approximately 3 per cent less of the variation in the data than the previous model in Section 4.1.

5.5. Model validation: Predicted distress in 2012

Estimating the model based on the supervisory diamond excluding data for the financial statements for 2011 results in a model where the variables are statistically significant with the same signs. Using the probability level of 7 per cent 12 out of 23 distressed banks are identified and 58 incorrectly classified distresses. Using the estimates on the out of sample financial statements for 2012 the model identifies 1 of the 3 distressed banks and not the other 2 distressed banks in 2012, i.e. the same result as in the model in Section 4.3.

The purpose of the supervisory diamond is to prevent excessive risk taking in banks. Some of the benchmarks can be difficult to change over a short period of time. In the models the probabilities of distress are estimated for the successive year; however, this might be too short a period of time to rectify for a bank facing problems. Therefore, the model is also estimated with a longer lag, representing a case where the authorities have time to react earlier to signs of problems.

If the model is estimated with the variables lagged 1 year none of the variables are statistically significant. If the model is estimated with the variables lagged 2 years only large exposures are statistically significant at the 10 per cent level of significance. In the model estimated with the variables lagged 2 years the number of observations is reduced to 420 of which 25 are distressed banks, cf. Table 8. 1 distressed bank is omitted in this model because data from the Danish FSA dates back to 2005.

If the model with a lag of 1 year is estimated on the same data as the model estimated with the variables lagged 2 years, i.e. leaving out the observations for 2006 (based on 420 observations) a similar number of correctly classified distresses is obtained as in the model with 2 year lag in the variables. This means that there are some observations in the data that the model cannot explain.

If the model is estimated with the variables lagged 3 years the number of observations is reduced to 325 of which 16 are distresses. All the variables are statistically insignificant and no distressed banks are identified at the threshold level of 7 per cent.

6. Conclusion and scope for further research

This paper examines leading indicators of Danish banks becoming distressed du-

Table 8. Supervisory diamand, lagged variables and final model.

Lag	Correct classification: Correctly classified distresses	Correct classification: Correctly classified non-distresses	Incorrect classification: Incorrectly classified non-distresses	Incorrect classification: Incorrectly classified distresses	Total	Distresses, total	Pseudo-R^2	AUC
No lag	13	431	55	13	512	26	0.1034	0.788
With 1 year lag	1	468	18	25	512	26	0.0110	0.563
With 2 year lag	4	325	70	21	420	25	0.0220	0.571
With 3 year lag	0	274	35	16	325	16	0.0292	0.607

Note: Probability level at 7 per cent. The model with no lag equals the model in Table 7, step 4. See note to Table 2 for a description of AUC. Pseudo-R^2 equals SAS® output max re-scaled R-square.
Source: Own calculations.

ring the period around the global financial crisis. It is the first study of this type using Danish data. The study is, at the same time, limited to a particular time horizon, the particular regulatory framework and the economic conditions during the period. Bearing this in mind, lower excess capital, higher lending growth, higher property exposure, and a higher funding-ratio indicate a higher probability of distress. Lending growth and property exposure relate in particular to credit risk whereas the funding-ratio relates to liquidity risk. Excess capital indicates the size of the buffer the bank has to cover losses. It takes a few years before a high lending growth affects the financial statements in a way that results in a higher probability of distress which is also found in related literature, cf. Logan (2001).

The supervisory diamond was introduced in 2010. The purpose is to help limiting risks building up in the banking sector going forward. In order to evaluate the supervisory diamond in an ex post experiment, we estimated a model where the explanatory variables comprise a constant term as well as the values of the five benchmarks adjusted with the limit values set in the supervisory diamond. The purpose of this estimation is to assess whether the variables in the supervisory diamond differ from the unrestricted model. The results of this model show that deviations from the benchmarks concerning property exposure and funding-ratio are statistically significant with expected signs. However, deviations from the benchmarks concerning lending growth, large exposures, and excess liquidity cover are statistically insignificant. The model describes the variation in the data to a less extent than the unrestricted model.

The unrestricted model uses average lending growth through 3 years lagged 2 years and finds that it is statistically significant while the supervisory diamond uses the yearly lending growth which is not statistically significant. This means that during the period leading up to the crisis, it was rather several years of high lending growth that caused problems for the banks than high lending growth in a single year and it takes a couple of years before it results in a higher probability of distress. However, the supervisory diamond now sets a limit for yearly lending growth and will thus in the future limit higher yearly lending growth persisting over several years. Another important difference is that excess capital is comprised in the unrestricted model and not part of the supervisory diamond. Even if the restricted model does not capture distressed banks as well as the unrestricted model, we argue that the analyses presented here support the establishment of benchmarks, like the supervisory diamond, as the unrestricted model identifies several of the variables entering the supervisory diamond,.

The model is estimated for one specific time horizon; the period around the global financial crisis. It would be interesting to estimate a similar model for a longer period of time encompassing more business cycles and the Danish banking crisis in the beginning of the 1990s. Another interesting expansion would be to estimate the model for different countries so as to allow for comparisons of the effects of different stages in the business cycles as well as regulatory frameworks and practices.

7. Appendices

7.1. Appendix 1: Distressed banks in FSA groups 1, 2 and 3, January 2008-December 2012. By year of announcement

Banks	Year
Distressed banks	
Sydbank and bankTrelleborg merged in March 2008 with Sydbank as the continuing company	2008
Roskilde Bank failed in August 2008. Initially, the bank's activities were transferred to Danmarks Nationalbank and the Danish Contingency Association, but later transferred to the Financial Stability Company	2008
Vestjysk Bank and Bonusbanken merged in October 2008 with Vestjysk Bank as the continuing company	2008
Morsø Bank and Sparekassen Spar Mors merged in November 2008 with Morsø Bank as the continuing company	2008
ebh bank failed in November 2008. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 1	2008
Handelsbanken and Lokalbanken i Nordsjælland merged in April 2009 with Handelsbanken as the continuing company (announced 15 September 2008)	2008
Nykredit Bank and Forstædernes Bank merged in April 2010 with Nykredit Bank as the continuing company. (announced 15 September 2008)	2008
Vestjysk Bank and Ringkjøbing Bank merged in December 2008 with Vestjysk Bank as the continuing company	2008
Løkken Sparekasse failed in March 2009. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 1	2009
Gudme Raachou Bank failed in April 2009. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 1	2009
Fionia Bank failed in May 2009. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 1	2009
Capinordic Bank failed in February 2010. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 1	2010
Sparekassen Lolland and Finansbanken merged in March 2010 with Sparekassen Lolland as the continuing company	2010

Eik Bank Danmark failed in September 2010. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 1	2010
Max Bank and Skælskør Bank merged in September 2010 with Max Bank as the continuing company	2010
Morsø Sparekasse and Aktieselskabet Morsø Bank merged in November 2010 and at the same time changed their name to Fjordbank Mors	2010
Amagerbanken failed in February 2011. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 3	2011
Sparekassen Midtfjord and Sparekassen Himmerland merged in February 2011 with Sparekassen Himmerland as the continuing company	2011
Fjordbank Mors failed in June 2011. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 3	2011
Max Bank failed in October 2011. The bank's activities were transferred to the Financial Stability Company under Bank Rescue Package 4	2011
Sparekassen Limfjorden and Sparekassen Vendsyssel merged in January 2012 with Sparekassen Vendsyssel as the continuing company	2011
Sparekassen Farsø and Den Jyske Sparekasse merged in March 2012 with Den Jyske Sparekasse as the continuing company	2012
Sparekassen Østjylland failed in April 2012. The bank's activities were transferred to Sparekassen Kronjylland and the Financial Stability Company under Bank Rescue Package 4	2012
Aarhus Lokalbank and Vestjysk Bank merged in March 2012 with Vestjysk Bank as the continuing company	2012
Spar Salling Sparekasse failed in April 2012. The bank's activities were transferred to Den Jyske Sparekasse with compensation from the Guarantee Fund for Depositors and Investors	2012
Tønder Bank entered 2 November 2012 an agreement with Sydbank. The bank's assets and liabilities – less equity and subordinated debt – were transferred to Sydbank	2012

7.2. Appendix 2: Descriptive statistics – by CAMELS and supervisory diamond.

Median of explanatory varables, non-adjusted

Variable	All banks	Non-distressed	Distressed	Expected sign
Capital adequacy				
Excess capital in per cent of RWA	6.6	6.8	3.9	-
Excess capital in per cent of requirement	72.4	75.2	38.6	-
Excess capital in per cent of loan and guarantees	6.4	6.5	3.8	-
Tier 1 ratio	14.3	14.5	9.4	-
Core tier 1 capital in per cent of RWA	13.8	14.1	8.0	-
Core tier 1 ratio less requirement, per cent	4.6	4.9	-0.8	+
Leverage ratio, total assets	5.4	5.3	9.5	+
Leverage ratio, loan and guarantees	7.9	7.7	12.5	+
RWA in per cent of total assets	86.2	86.5	84.8	+
Individual capital need	8.9	8.8	10.4	+
Total capital ratio	16.2	16.3	14.3	-
Asset quality				
Lending growth 2005-08 (including loan impairment charges), annual average	22.9	22.7	32.0	+
Lending growth 2008- (before loan impairment charges), annual average	8.7	8.4	10.4	+
Accumulated lending growth 2005-08 (including loan impairment charges)	70.3	68.6	119.4	+
From 2005-2008: Accumulated lending growth 2005-2008 (including loan impairment charges), After 2008: Accumulated lending growth 2008-(including loan impairment charges)	16.2	16.0	18.3	+
Lending growth, latest quarter (including loan impairment charges)	1.6	1.6	1.4	+
Lending growth, latest year (including loan impairment charges)	8.8	8.8	10.1	+
Lending growth, latest year (excluding loan impairment charges)	7.7	7.9	5.8	+
Average annual 3 year lending growth	13.5	13.5	13.0	+
Average annual 3 year lending growth, lagged 1 year	15.6	15.4	23.2	+
Average annual 3 year lending growth, lagged 2 years	16.2	15.9	25.0	+
Average annual 3 year lending growth, lagged 3 years	15.5	15.3	24.1	+
Property exposure	11.5	11.3	22.2	+
Agricultural sector exposure	8.4	8.4	7.2	+
Concentration index (Herfindahl) by sector	25.4	25.5	20.9	+
Large exposures	65.6	63.0	112.8	+
Large exposures in per cent of excess capital	1.5	1.5	3.8	+
Loan impairment charge ratio, latest quarter	0.7	0.6	1.8	+

continues ...

continued ...

Variable	All banks	Non-distressed	Distressed	Expected sign
Loan impairment charge ratio, accumulated	2.4	2.4	4.4	+
Impaired loans ratio in per cent of loans, (ILR)	5.3	5.1	9.6	+
Management				
Deposit growth, 12 months	9.1	8.9	11.3	-
Costs less loan impairment charges, per cent of income	67.1	67.1	67.3	+
Costs including loan impairment charges, per cent of income	88.1	87.7	108.1	+
Annual growth in total assets	8.6	8.6	-8.5	-
Size (logarithm of total assets)	8.2	8.1	8.6	-
Implicit deposit rate	0.5	0.5	0.6	+
Implicit lending rate	1.8	1.8	1.8	-
Implicit deposit rate less reference rate	-2.8	-2.8	-0.6	+
Implicit lending rate less reference rate	-1.5	-1.5	0.2	-
Implicit interest margin	1.2	1.2	1.1	-
Earnings				
Return on equity after taxes, latest year	4.1	4.4	-5.5	-
Return on equity before taxes, latest year	3.5	3.6	-4.7	-
Return on equity after taxes, latest quarter.	-0.1	-0.1	-3.1	-
Return on equity before taxes, latest quarter.	0.0	0.1	-2.7	-
Return before taxes in per cent of RWA	4.6	4.9	-0.8	-
Liquidity				
Excess liquidity cover	150.6	151.1	138.2	-
Funding-ratio, less repo transactions	0.8	0.7	0.8	+
Funding-ratio, including repo transactions	0.8	0.8	0.9	+
Deposits in per cent of lending, less repo transactions	0.9	0.9	0.8	-
Deposits in per cent of lending	0.9	0.9	0.8	-
Debt to credit institutes in per cent of average total assets	13.9	13.9	14.4	+
Sensitivity to market risk				
Interest rate risk	2.0	2.0	1.5	+/-
Supervisory diamond				
Lending growth, deviation from limit value	-12.3	-12.1	-14.2	+
Property exposure, deviation from limit value	-13.5	-13.7	-2.8	+
Large exposures, deviation from limit value	-59.4	-62.0	-12.3	+
Funding-ratio, deviation from limit value	-0.2	-0.3	-0.2	+
Excess liquidity cover, deviation from limit value	100.6	101.1	88.2	-

Note: »+/–« in the expected sign column indicates that the expected sign of the variable is ambiguous.

7.3. Appendix 3

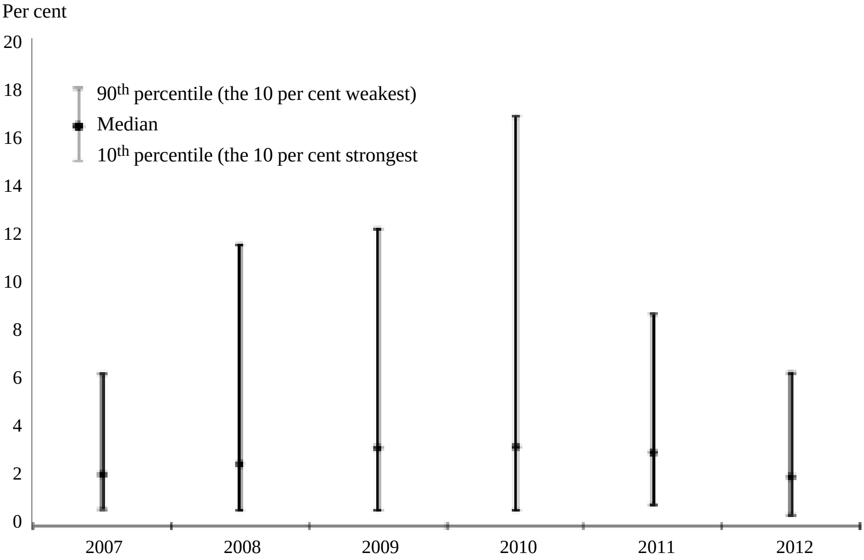

Figure 4. Estimated probability of distress, unrestricted model including sector's average 3 year lending growth lagged 2 years.

Note: The probability of distress at year-end.

7.4. Appendix 4

Classification table, supervisory diamond.

	Correct classification		Incorrect classification		Percentages				
Probability level	Distress	Non-distress	Distress	Non-distress	Correct classification	Sensitivity	Specificity	Incorrect classification	Incorrect classification
0.01	26	0	486	0	5.1	100	0	94.9	–
0.013	26	0	486	0	5.1	100	0	94.9	–
0.02	26	10	476	0	7	100	2.1	94.8	0
0.03	23	134	352	3	30.7	88.5	27.6	93.9	2.2
0.04	22	269	217	4	56.8	84.6	55.3	90.8	1.5
0.05	17	366	120	9	74.8	65.4	75.3	87.6	2.4
0.06	13	414	72	13	83.4	50	85.2	84.7	3
0.07	13	431	55	13	86.7	50	88.7	80.9	2.9
0.08	8	451	35	18	89.6	30.8	92.8	81.4	3.8
0.10	3	462	24	23	90.8	11.5	95.1	88.9	4.7

Note: Cross-validated probabilities. Sensitivity equals estimated distress relative to actual distress. Specificity equals estimated non-distress relative to actual non-distress.

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