THE EFFECTIVENESS OF CAPITAL ADEQUACY MEASURES IN PREDICTING BANK DISTRESS†

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Abstract:

Our concern in this article is two-fold: first to see whether the determinants of bank distress and failure have been any different in the GFC from previous years: second to see whether simple measures of capital adequacy outperform their risk-weighted counterparts as predictors, despite the focus on the later in the Basel framework. This paper examines bank distress within a large quarterly data set of FDIC insured US banks from 1992 to 2012. We contrast two methods, the logit technique and discrete survival time analysis, to predict bank failures and draw inferences about the stability of contributing bank characteristics. The models incorporate CAMELS indicators that consider the bank-specific variables and macroeconomic conditions. We contrast risk-based and non-risked-weighted measures of capital adequacy. We find that the non-risk-weighted capital measure, the adjusted leverage ratio, explains bank distress and failures best. The logit model is able to distinguish failing from healthy banks with an accuracy of 80%. The corresponding survival time model achieves 98%. Further, we find evidence that the influence of the characteristics in the two methods differ only slightly. The characteristics of banks getting into bank distress do not change over time in this sample. That means that the familiar banking characteristics for identifying a distress-prone bank identified fragile banks effectively during the global crisis without new information and are likely to continue to work well in the future.

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Introduction

Basel III, in its efforts to provide comprehensive capital buffers against losses in banks has added a leverage ratio to the revised risk-weighted buffers that characterised both Basel I and Basel II (Basel Committee on Banking Supervision (BCBS), 2011). Some countries, Australia and New Zealand among them, have announced that they do not plan to introduce the leverage ratio (Australian Prudential Regulation Authority (APRA), 2012; Reserve Bank of New Zealand (RBNZ), 2011) They argue inter alia that the leverage ratio is a crude measure and at the value chosen will not add anything useful to more sophisticated measures and might imposed an unnecessary cost on the banks. Others promote a diametrically opposed view, that if any capital buffer is to be used it should be a leverage ratio, preferably one that catches off-balance sheet activity (Joint Shadow Financial Regulatory Committee (JSFR), 2011; Shadow Financial Regulatory Committee (SFRC), 2012). The main argument advanced is that not only is leverage typically what leads to fragility in banks but that it is readily observed and difficult to evade if equity is measured properly. In other words, it is its crudeness which is its advantage. The arguments of this camp have been greatly strengthened by Andrew Haldane's presentation to the 2012 Jackson Hole Conference (Haldane & Madouros, 2012), where he argues that simple rules such as the leverage ratio work better as indicators of problems, based on a subset of the data we use here.[1] As Haldane (2011, p. 3)puts it: 'complex systems typically call for simple control rules.'

There is also some empirical evidence that simple leverage ratios are better indicators of potential bank distress (Estrella, Park, & Peristiani, 2000). However, there is clear empirical evidence from the global financial crisis (GFC) and earlier that risk-weighted capital buffers were not good predictors in practice. Hau, Langfield, and Marques-Ibanez (2012, p. 3) argue that 'basel risk-weights applied to claims on institutions do not reflect underlying relative risk.' Northern Rock for example was fully compliant with risk-weighted measures shortly before its failure (Mayes & Wood, 2009). Its leverage ratio was however extreme and would not have met the Basel III criterion (Shin, 2009). Nevertheless, it could be that much of the problems with banks in the GFC was with authorities not reacting to signs of danger rather than the danger signs not being present. Using evidence from the Material Loss Reviews, Garcia (2012), for example, points out

[1] On the basis of an international dataset, Mariathasan and Merrouche (2012)also support this position, when they argue that there is evidence that more fragile banks tend to manipulate risk-weighted measures, thereby helping to obscure their true position from both the authorities and their current and potential creditors, when the bank is under threat. Hence while risk-weighted measures may be better indicators in normal times they perform worse than the simple leverage ratio once problems appear on the horizon.

that supervisors in the US missed the normal 'red flags'. Hence it was not the flags which were at fault.

In this paper we therefore investigate both whether traditional indicators could predict distress and failure in banks during the GFC and whether a simple leverage ratio works better than other measures of capital adequacy. We use a comprehensive quarterly dataset of banks in the US over the period 1992 to the second quarter of 2012. However, we begin by surveying the evidence from the existing literature both across countries and types of banks and across the different parametric and non-parametric methods that have been used (Section 1). In the light of this we use both a logit/probit approach and a survival (hazard) approach to check for robustness. Section 2 considers the characteristics of the data we use from the FDIC, while Section 3 sets out the main results from the estimation of both models. Since the main point of this exercise is to explore the forecasting ability of these models, this is subject of Section 4. Section 5 contains a set of robustness tests to see if the model is stable and the degree to which it suffers from omitted variables. Section 6 offers some conclusions and policy implications.

1 Previous Evidence

We begin by a meta-analysis of previous work on the subject, which is summarised in Table 1, in order to determine the most plausible approaches to use and the variables to include. We are concerned for our approach to be robust to a variety of methods and not dependent on a single model, so as to increase the generalisability of the conclusions.

1.1 Early Warning Systems

Over recent decades, a considerable literature has been devoted to explaining financial distress and failure of financial institutions, especially banks. Due to the uniqueness of banks and their potential fragility, determining which banks are likely to default or experience distress is a long-standing but still important concern. First, the findings assist banking supervisors and regulators in their task of maintaining a prudent and stable system. Second, the early detection of potential problems is likely to help reduce the expected cost of a bank failure and to decrease the chance of the problem spreading more widely through the financial system. If the characteristics of potential distress can be identified, this helps the authorities to focus their limited resources. To be useful the predictions need to be sufficiently accurate to avoid wasting too much time on sound banks and yet to avoid missing too many problem cases. Since most banking regulatory and supervisory authorities employ such early warning systems (EWS), apparently they find them sufficiently useful.[2] Nevertheless, there is considerable scope for improvement as the number of surprise failures in the global financial crisis suggests.

In the late 1970s the Federal Deposit Insurance Cooperation (FDIC) in the US developed and implemented an EWS to assess the financial, managerial, and operational strength and weaknesses of financial institutions. Its quality and success is demonstrated by the fact that this model provides the framework for empirical research on the topic and for most systems implemented in other countries. The EWS is characterised by a set of ratios obtained from financial statements (although not all the information is publicly available). These ratios are classified into six categories: capital adequacy (C), asset quality (A), management competence and expertise (M), earning ability and strength (E), liquidity (L) and sensitivity to market risk (S), jointly referred as CAMEL(S).[3] For each component the regulatory authority assigned a rating using a scale from 1 (good) to 5 (bad), where ratings of 1 or 2 are considered to present no or little supervisory concern and ratings of 3-5 are the subject of moderate to major concern. These individual scores are combined to provide an overall rating also with a scale from 1 to 5. An overall rating of 3 to 5 alerts the supervisors and the bank could face intervention by them.[4] CAMELS-ratings prepared by the FDIC are not public. The development and the implementation of similar EWS in Europe took until the early 1990s and a substantial number of EWS have now been developed round the world.

In recent years considerable effort has gone into improving EWS – starting well before the global financial crisis. While the generality of experience relating to failures may not change over the time, models and techniques have changed. The models used have been much better at explaining failures within the data set in their estimation than they have been at predicting new and as then unobserved failures. The ratios as well as the weighting of the individual indicators changed over the time. Behaviour by banks is likely to have a degree of endogeneity. Once banks understand how their fragility is being assessed they have a strong incentive to meet the criteria laid down while still pursuing their original strategies as far as they can.[5] This change in their behaviour will make the prediction methods less effective and hence the EWS will need to be enhanced. If the components of the early warning systems have changed over the time and these

[2] For an extended review on this use of EWS see Evens, Leone, Gill, and Hilbers (2000).
[3] Until 1996 the component of market risk was not included in the model, so it was then referred to as the CAMEL system. For more information see Flannery (1998) and Jose (1999).
[4] For detail information on the functioning of the rating approach see Cole and Gunther (1995a).
[5] Mariathasan and Merrouche (2012)suggest that banks in trouble systematically try to massage their key ratios so that they obscure the true extent of their difficulties.

changes provoke adjustments to models, there will be no general model that performs well in predicting failures and distress over a long time period. Although every distress or failure period is different, most are characterised by some patterns. The goal of the models is mostly to find these patterns and to enable accurate prediction of bankruptcy. Prediction models have become more sophisticated over time and more complex and interdisciplinary. As a result models are becoming more difficult to interpret – going beyond their private usefulness in the view of Haldane and Madouros (2012).

It is not surprising that absolute levels of risk may have been underestimated in the run up to the global financial crisis. It is always difficult to decide how much any upturn reflects enduring changes and how much simply a cyclical improvement that will disappear in due course. Natural optimism might suggest an upward bias but Hau, Langfield, and Marques-Ibanez (2012)suggest that rating agencies have a relative bias as well. The same conflicts of interest that may contribute to this bias do not apply to the authorities. Nevertheless it is likely that large institutions with any given degree of fragility are more likely to be able to persuade the authorities of their probity than their smaller counterparts, if only because they can afford better communicators and prima facie are more diversified. Thus ordinal as well as cardinal ratings of possible default are countercyclical according to Hau et al's analysis of 369 banks in the US and the EU15 (i.e. prior to the 'eastern' enlargement).

Over the years a wide variety of early warning systems have been developed. There are two main dimensions to these EWS

(i) the institutions and the markets they cover

(ii) the variables they include and the different channels of transmission they identify.

The early EWS mainly focused on individual banks level and were concerned with individual banking failures, but there are other EWS that consider the soundness of the whole banking or financial sector and try to predict systemic crises.[6] This paper deals only with the individual banking level, where most models are of the CAMEL(S) variety. However, EWS at the financial sector level do often have important findings that are relevant for bank level studies.[7]

[6] We focus here only on models that have been published and rely on publicly available data. Supervisors' internal models, particularly those making use of confidential information cannot, by their nature, be included.

[7] Davis and Karim (2008), Demirguc-Kunt and Detragiache (1998), Gaytán and Johnson (2002), Gonzalez-Hermosillo (1999), and Hardy and Pazarbasioglu (1998) offer excellent reviews of these early warning systems for banking crises.

The original CAMEL model focuses on accounting and financial data for individual banks.[8] Some authors also added macroeconomic data to capture economic pressures and shocks that could trigger a banking failure or to cover divergence in cross country studies. Variables such as GDP growth, inflation, inter-bank interest rates or exchange rates are included to capture those effects.[9] (The final column of Table 1 lists these extra variables for each study.) There is also a strand of literature that uses market data and information. Flannery (1998) was probably the first to add market information, driven by market forces and discipline, including price-based indicators such as market expectations through stock prices, volatility of returns and bond spreads.[10] Market information-based approaches are only applicable for publicly listed and traded banks, however, in most countries the majority of financial institutions are not publicly traded, although the majority by value of deposits are. There are other non-accounting or market information indicators and information that can be taken into account instead, such as rating agency assessments. The idea is to capture the effects of risk and financial strength that are reflected in other indicators.[11] There are indicators of depositor behaviour and bank credit ratings of ratings agencies for example.

1.2 Model Approaches

We begin our meta-analysis (Table 1) by classifying the estimation methods, shown in column 2 of the table. Predominantly, models have used financial statements as their data source.[12] Only two main groups of failure and distress prediction methods: statistical and non-parametric techniques, seem to have been used.[13] Although there is no single agreed definition of what constitutes failure or distress nor of the indicators to be used for it, which include insolvency, incidence of intervention or closure and assisted merger or acquisition. Hence comparison of models can readily neglect their detail.

<u>Statistical estimation techniques</u>

[8] For instance, these model type is employed by Avery and Hanweck (1984), Cole and Gunther (1995b), Cole and Gunther (1998), Estrella, Park, and Peristiani (2000), DeYoung (2003), Martin (1977), Whalen (1991), and Wheelock and Wilson (2000).
[9] For implementation of macroeconomic or structural variables see Arena (2008), Halling and Hayden (2006), and Männasoo and Mayes (2005, 2009).
[10] See Bongini, Laeven, and Majnoni (2002), Campbell, Hilscher, and Szilagyi (2008), Chiak (2007), Curry, Fissel, and Elmer (2003), Curry, Elmer, and Fissel (2007), Hillegeist, Keating, Cram, and Lundstedt (2004), Jagtiani and Lemieux (2001), and Pettway (1980) for an application of these approach.
[11] See Kraft and Galac (2007), Poghosyan and Cihák (2009), and Avkiran and Cai (2012) for implementation of market information-based approaches.
[12] For a detailed review of various techniques see Aziz and Dar (2006), Demirgüç-Kunt (1989), Demyanyk and Hasan (2010), Fethi and Pasiouras (2009), Ravi Kumar and Ravi (2007), and Tatom and Houston (2011).
[13] Models sometimes use a combination of techniques, so that the classification is always not clear cut.

Statistical estimation techniques are the most widely used approach with discriminant analysis (DA) and logit/probit estimation being most common for cross-sectional methods. DA was the leading method originally. The idea is to model the dependent score variable for failures/distress as a function of input factors. A score is derived from a linear combination of independent predictive variables for each firm. Based on the sample, a cut-off point is defined so that banks with a score below the cut-off are expected to be in distress and accordingly the firms with a score above the cut-off are expected not to be in distress. This implies that input factors such the number of bad loans will be significantly different between failing and non-failing firms. However, discriminant allows more than just binary outcomes and can be extended to quadratic and *multivariate discriminant analysis* (MDA). This analysis combines linearly multiple discriminant characteristics and variables within one model. The score of a (M)DA can be set out as follows:

$$F_i = a_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n, \tag{1}$$

where F_i is the failure score for a given institution *i*, a_0 is the intercept, and b_i are regression coefficients and x_i are the characteristics. However, DA studies are no longer normally used. One major drawback was the restrictive assumptions of normally distributed regressors and the covariance matrices of the groups having to be identical. In any case multiple discriminant analysis is really only about classifying firms and not about estimating the risk of defaults (Eisenbeis, 1977). Furthermore, there are questions about the reliability of the discriminant analysis due to the restrictions of the model (Ohlson, 1980).

These critiques led to the emergence and increasing use of an alternative statistical approach, limited dependent variable models. These binary models apply a linear regression technique to estimate the probability that a particular outcome such as a bank failure occurs:

$$\mathrm{D_i} = \begin{cases} 1 \text{ if bank i fails} \\ 0 \text{ otherwise} \end{cases}. \tag{2}$$

These methods take a number of forms. The simplest is the *linear probability model*. The linear probability model determines the individual score or outcome for each dependent variable D_i:

$$\mathrm{D_i} = \mathrm{X_i}\beta_i + \mathrm{u_i}\,, \tag{3}$$

where X_i reflects the given set of individual characteristics for observation *i,* $\beta_i{}'$ represents the vector of coefficients and u_i is the disturbance term. The probability P_i that a failure event occurs for observation *i* is given by:

$$\mathrm{P_i} = Pr(\mathrm{D_i} = 1) = \mathrm{X_i}\beta_i + \mathrm{u_i}. \tag{4}$$

The coefficients obtained have to be interpreted in terms of probability. In addition to other shortcomings, this model formulation has the dominating disadvantage of assuming a normal distribution and not ensuring that the values obtained lie between zero and one, which is necessary for probability estimates.

Two other approaches, probit and logit models, can overcome this shortcoming and provide a transformation of the regression function ensuring that probability values are between zero and one. These employ statistical estimation methods such as maximum likelihood that are much more flexible than simple linear estimation techniques. The probit and logit models differ only in their assumed distribution. In both models the outcome probability is very sensitive to changes in variables. The *logit model* assumes a logistic distribution. Equation (3) is transformed into a logit function F_i. The general logit model and its given cumulative probability distribution are given by the following expressions:

$$F_i = \frac{e^{\mathrm{D_i}}}{1 + e^{\mathrm{D_i}}} = \frac{1}{1 + e^{-\mathrm{D_i}}} \tag{5}$$

$$F_i(\mathrm{D_i}) = F(X_i \beta_i' + u_i) = \frac{1}{1 + e^{-\mathrm{D_i}}}\,. \tag{6}$$

The *probit model* on the other hand assumes a standardized normal distribution. Equation (3) can also be transformed into a cumulative standard normal function:

$$F_i = \Phi(\mathrm{D_i}) = \int_{-\infty}^{z_i} \frac{1}{\sqrt{2\pi}} e^{\left(\frac{-\mathrm{D_i}^2}{2}\right)} d\mathrm{D_i} \tag{7}$$

$$F_i(\mathrm{D_i}) = F(X_i \beta_i' + u_i) = \int_{-\infty}^{z_i} \frac{1}{\sqrt{2\pi}} e^{\left(\frac{-z_i^2}{2}\right)} d\mathrm{D_i}\,. \tag{8}$$

This ensures that the estimated probability lies between zero and one.

There is also another statistical technique that focuses on the time series dimension of failures: *survival time analysis*. The idea is not just to estimate the chance of failure by a bank but also to determinate the specific time period when it occurs and to investigate the change in probability of a failure over the time. There is a wide variety of different approaches. For banking failure the Cox (1972) proportional hazard model had dominated. This model, popularized by Kiefer (1988), applies parametric and non-parametric input factors and models the time of failure as the dependent variable. In a proportional hazards model the dependent variable is the time until failure T_i. The survivor function $S_i(t)$ represents the probability of surviving longer than t periods and has the following form:

$$S_i(t) = Pr(T_i > t) = 1 - F_t \, , \tag{9}$$

where F_t represent the cumulative distribution function of the random variables *t*, which is the number of survived periods. The general form of the hazard function can be described as the limit of the condition probability that indicates the propensity to fail:

$$h_i(t) = \lim_{dt \to 0} \frac{Pr(t < T_i < t + dt \,|t \leq T_i)}{dt} = -\frac{S_i^{|}(t)}{S_i(t)} . \tag{10}$$

This formulation represents the failure probability at a given time period conditional on the observation has survived to period *t*.

The formulation of the Cox (1972) proportional hazard model is the following:

$$h_i(t|\mathrm{X_i}\beta_i^{'}) = h_{0,t} \exp(\mathrm{X_i}\beta_i^{'}) \, , \tag{11}$$

where is $h_{0,t}$ is the baseline hazard and β_i is the vector of unknown regression coefficients.

Non-parametric and distribution-free estimation techniques

The two most popular ideas in this field are the artificial neural network (ANN) and data envelopment analysis (DEA). *Artificial neural networks* have been used to model banking failures since the beginning of the 1990s. In contrast to statistical approaches, this non-linear approach is able to capture non-linear effects such as the saturation effects. But these models need a large range of input data to perform well and have problems with extreme observations which is the major drawback of the method. Use of the ANN idea goes back to McCulloch and Pitts (1943). The way it works is inspired by the biological nervous system. Odom and Sharda (1990) are among the first to employ ANN for bankruptcy studies. They conclude that this technique outperformed multiple discriminant analysis by using the same variables. The basic computational structure of an ANN is based on three layers: input, hidden and output. The ANN tries to capture the connections of these layers. This system needs to learn patterns from available training data (in-sample) sets to perform in the total sample data well. Although no assumptions are imposed on the form of input/output functions or the need of continuous and differentiable form, the following formulation is used to model ANN (Tam & Kiang, 1992):

$$I_i = \sum_j w_{ij} \, O_j + \phi_i \tag{12}$$

$$O_i = \frac{1}{1 + e^{I_i}}, \tag{13}$$

where I_i is the input of *i*, O_i is the output of *i*, w_{ij} is the connection weighted between the *i* and *j*, and ϕ_i is the bias of *i*.

Data envelopment analysis (DEA) aims at determining production efficiency by transforming a given input factor into given output factors by linear programming techniques. Due to the non-parametric approach, there is no equation that describes the relationship between the input and output factors. DEA is often used for banking benchmarking purposes and only rarely to predict banking failures. An exception is Avkiran and Cai (2012), who show in a multi-dimensional environment that it is the least 'efficient' banks that fail.

Given this wide range of potential estimation techniques for predicting banking failures that have been used in practice, we use the two approaches that have been followed most widely in recent years, logit and time survival analysis, in our analysis in order to ensure the maximum of comparability with earlier work. This also enables us to encompass a wide range of the previous research These two techniques also have the advantage of simplicity, comprehensibility and manageability in estimation. Our choice also reflects the finding that these approaches seem to be most appropriate when handling large data sets both in terms of number of determining factors and numbers of banks. However, these methods do have well-known problems. The logit model results are relative sensitive to variable choice.. The survival time analysis technique has an issue with extreme events. But exactly these events often determine bank failure. This problem could be addressed by data transformation. The hazard model is also not able to differentiate between different failure processes from the same population. However, this problem should be limited with an increasing number of observations.

There is considerable appeal in the non-parametric and distribution-free estimation techniques such as neural networks or DEA as these studies have introduced degrees of complexity and sophistication to modelling failures. However the benefit of this complexity in the present context is of mixed value, since the model accuracy does not improve significantly. These new model types also have substantial data requirements and seem not to be applicable over a long time periods or large data sets. Non-parametric models have hence often only been applied to a small number of observations over a small time period and to specific data. Nevertheless it may well be worth expanding the range of techniques we use in subsequent analysis.

1.3 The Choice of Determining the CAMELS Components

We now move from our choice of modelling technique to the choice of variables to include in the analysis. We have used the six CAMELS categories in Table 1 to classify the choices in previous work, as this format characterises not just most academic studies but. also those commonly applied by supervisory authorities (Sahajwala & Van den Bergh, 2004). Despite the considerable variety of variable choice, and may divergence in effects and significance in the results, there is considerable similarity. Although no uniform way of deciding upon which indicators to be included has been adopted, there is considerable homogeneity over which characteristics are good indicators of financial distress. However, one reason for following the layout of Table 1 is that the influencing factors may not be stable throughout time and across different markets. Unfortunately the problem is confounded because researchers have learned by experience at the same time that behaviour may have changed. So it is only where authors go back over a long enough dataset that they can show whether the change lies in the data rather than in the model.

We take the six categories in their order in CAMELS and this is repeated across the columns of Table 1.

Capital adequacy. Not only does capital adequacy come first in the list but it is the key variable considered important in the Basel framework for ensuring healthy banks. Bank's capital serves as a cushion to absorb losses and shocks. The decline in capital relative to assets is as an indication for potential financial difficulties. Not surprisingly, nearly all previous research has included such measures (Table 1). Due to the large amount of information disclosed and the different definitions of equity there is a wide variety of potential measures. The most important distinction can be made in the weighting of risks. In the Basel framework the weighting is determined by risk-sensitivity ratios for each asset group and has to be authorised by the regulatory body. Although these risk-weighted capital ratios measures are often used, for example, in Poghosyan and Cihák (2009), the ratios face a clear drawback. They are open to manipulation and provide space for discretion to cover up the real condition of the bank.[14] Accordingly, other studies employ non-risk-weighted capital ratios.[15] The potential benefit is the avoidance of any risk assessment. We apply both risk-weighted and unweighted capital measures in estimating the potential effects to financial distress and to find the most adequate measure as part of the

[14] See Das and Sy (2012), and Le Leslé and Avramova (2012) for more information on the issues of risk-weighted assets.

[15] This includes Avkiran and Cai (2012), Cole and Gunther (1995b), Curry, Fissel, and Elmer (2003), DeYoung (2003), Poghosyan and Cihák (2009), Männasoo and Mayes (2009), and Tatom and Houston (2011).

rationale behind the study is to determine which has worked better in the circumstances of the global financial crisis.[16]

Assets and their quality. The condition and quality of individual asset categories can trigger financial problems and act as an important accelerator of bank fragility. By holding qualitatively inferior assets, the bank is more vulnerable to losses. Recognising these losses requires write downs and hence reduces the capital cushion. As a consequence of the capital loss the risk of failure increases. Due to the wide spread of banks' activities and the range of asset figures disclosed, there is a wide variety of potential indicators. Since the dominating business of commercial banks and thrifts is lending, it is reasonable to focus on this asset group. A potential measure of loan quality is to gauge the amount of provision to loan losses as in Poghosyan and Cihák (2009). As a reaction to higher expected loan losses banks are forced to make higher provisions. But by inverting the argument a higher provision cannot be traced uniquely backed to loan quality. Hence, another assessment might be more useful. The non-performing loan ratio, measured as non-performing loans[17] to total loans, is more helpful, since the definition is more generalised, and is frequently used in the literature. [18]

Management competence and expertise. The ability and skill of the bank management play a crucial role in the performance and success of the institution. The higher the management competence, the lower is the vulnerability of the bank and the likelihood of making wrong decisions. Although this relationship is well-founded, the influence is hard to capture with financial data. As Table 1 shows, recent studies have implemented this component less frequently than the others. Mostly, researchers adapt and derive figures from other CAMELS categories such as earnings or asset quality indicators to approximate the management's efficiency and profitability. [19] Other models use accuracy measures such as efficiency in the DEA approach.[20] It is difficult to find an independent indicator. However, Lane, Looney, and Wansley (1986) and Wheelock and Wilson

[16] Clearly our choice of variables is constrained by the data set we use – the FDIC statistics on depository institutions (SDI) – but the choice of this dataset is itself largely driven by the very large range of information available, which permits a real choice of indicators in most cases.

[17] The IMF (2005) defines "a loan is nonperforming when payments of interest and/or principal are past due by 90 days or more, or interest payments equal to 90 days or more have been capitalized, refinanced, or delayed by agreement, or payments are less than 90 days overdue, but there are other good reasons —such as a debtor filing for bankruptcy—to doubt that payments will be made in full.".

[18] See Alam, Booth, Lee, and Thordarson (2000), Henebry (1997), Halling and Hayden (2006), Tatom and Houston (2011), and Whalen (1991) for an application of the non-performing-loan ratio.

[19] See for instance Halling and Hayden (2006) (earnings) and Cole and White (2012), Henebry (1997) and Thomson (1991) (asset quality indicator).

[20] For the application of the DEA approach see Barr, Seiford, and Siems (1993); Barr and Siems (1994), and Tatom and Houston (2011).

(2000) incorporate measures of management efficiency that are also frequently used in practice. The FDIC provides also an efficiency ratio to assess the management quality. This efficiency ratio reflects expenses as a percentage of revenue.

Earning ability and strength. This category reflects the sustainability of earnings and profits. Higher levels of profitability should allow banks to improve their capital and economic performance. In general, there is a negative relationship between profitability and the likelihood of distress. Insufficient ability to maintain earnings leads a bank to make losses. These losses feed back on the amount of capital and asset quality. Since banks are required to disclose key figures of profit and loss statements, there are many possible ratios to use. It is essential to adjust for risk so that the measures of returns are sensibly comparable. Recent research has applied a wide variety of earnings indicators, but the common choice is profitability or accounting measures such as cost-to-income-ratio or ROA/ROE. [21] We follow this trend and use the net operating income to assets ratio to capture earnings strength.

Liquidity. Liquidity is essential for a bank's ability to meet and repay its short-term obligations and unexpected withdrawals of depositors and creditors. The amount of highly liquid assets is negatively correlated to the possible likelihood of distress. Recent studies have tried various ways of capturing these effects. One approach relates liquid assets such as federal funds or securities to total assets.[22] Other studies measure ratios between various types deposit/loans to assets.[23] A third well-used idea is the loan-to-deposit (LTD) ratio. [24] This well-known ratio indicates the percentage of loans funded through deposits and the stability of funding. Given the emphasis on the Net Stable Funding Ratio in Basel III we apply this ratio as a liquidity measure. Clearly it is only a good liquidity indicator for deposit-taking institutions.

Sensitivity to market risks. The concern is with the impact on banks from shifts and fluctuations in the financial market. These shifts cover not just price variations but also variations in funding. Banks are vulnerable to market distortions if they rely heavily on market refinancing or are holding highly volatile assets. As Avkiran and Cai (2012) remark and Table 1 shows this sixth

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[21] See for instance Alam, Booth, Lee, and Thordarson (2000), Arena (2008), Avkiran and Cai (2012), Curry, Fissel, and Elmer (2003), Cole and Gunther (1995b), Cole and White (2012), Henebry (1997), Männasoo and Mayes (2005, 2009), Poghosyan and Cihák (2009), Tatom and Houston (2011), and Wheelock and Wilson (2000).

[22] Cole and White (2012),Curry, Fissel, and Elmer (2003), and Wheelock and Wilson (2000) utilizes such liquid assets.

[23] For instance Henebry (1997), Männasoo and Mayes (2005, 2009), and Poghosyan and Cihák (2009) employ such ratios.

[24] This idea is pursued by Alam, Booth, Lee, and Thordarson (2000), Tatom and Houston (2011), and Whalen (1991).

CAMELS component has been widely neglected or ignored. This omission can be explained by difficulties in capturing this relationship with accounting and financial data. Therefore, some researchers use size of the bank as an approximation.[25] However, this proxy neglects the fact that business size is not strictly accompanied by market exposure. For example, a small savings bank has a low sensitivity and a small specialized trading bank a high market sensitivity. Of course, it is important to consider the size, but it is not satisfactory to replace the sensitivity component with the size indicator. Other researchers such as Männasoo and Mayes (2005, 2009) or Whalen (1991) use deposits ratios to capture this effect. Others think that it is more appropriate to measure the sensitivity as the bank's holding with volatile liabilities.[26]

Since the CAMELS model neglects political and economic factors along with bank strategies, some researchers implement further variables to take these influences into account.[27]

1.4 Relevant Recent Experience from CAMELS-related Studies

One of our main concerns in this article is that the global financial crisis may have revealed that the determinants of bank fragility have changed. Banking has evolved considerably in recent years, both with the move away from traditional deposit-based funding and the perceived changes in the risk environment under the 'great moderation'. Such studies as there are confirm the validity of the CAMELS approach. Curry, Fissel, and Elmer (2003) investigated US banking failures from 1988-95, applying the CAMELS approach in a logit framework. They found that considering publicly available market & financial information only marginal improve the accuracy of the model. Tung, Quek, and Cheng (2004) employed the CAMELS approach with the ANN technique. They were able to explain and predict financial distress very accurately over 1980-2000. Männasoo and Mayes (2005) employed logit technique with a five components CAMELS model and structural and macroeconomic factors in an Eastern European multi country data set from 1996 to 2003. They showed that in addition to bank-specific factors macroeconomic factors and institutional frameworks also played an important role in determining bank distress. They also found that the determinants of failure change the closer the crisis comes, because authorities and banks try to prevent it. In their subsequent work, Männasoo and Mayes (2009), support this finding by using a refined sample in a wider time span (1995-2004) and discrete time

[25] Abrams and Huang (1987), Avkiran and Cai (2012), Kolari, Glennon, Shin, and Caputo (2002), and Wheelock and Wilson (2000) use the size to approximate the sensitivity to market risk. This proxy also reflects the too-to-fail-issue that big banks are less likely to fail (Avkiran & Cai, 2012).

[26] See Evens, Leone, Gill, and Hilbers (2000)for more information on this aspect.

[27] For example Arena (2008), Cole and Gunther (1995b), Halling and Hayden (2006), Tatom and Houston (2011), and Tung, Quek, and Cheng (2004) implement further variables.

survival analysis. Halling and Hayden (2006) employ a four components CAMELS model using the survival time analysis technique for data from 1995-2002. The work also incorporated structural factors and performs well for a sample in Austria. There is an obvious tendency, which characterises our work as well, to focus on banking crisis periods and not consider normal periods, because this generates far more examples of failure, which aids estimation. This may bias the findings and limit their generalisability.

Poghosyan and Cihák (2009) include the early part of the GFC, using a logit model with all CAMEL categories to determinate bank failure in Europe from 1996-2008. They found consistent indicators that can help to identify banks that are vulnerable to financial distress. Jordan, Rice, Sanchez, Walker, and Wort (2010) used three CAMELS categories in combination with three institutional characteristics inside a MDA environment. They were able to predict bank distress in their three year data set (2007-10). Cole and White (2012) used logistic models and found that the traditional CAMEL approach worked adequately during the financial crisis. This finding is supported by Jin et al. (2011), who used only two CAMELS categories with other accounting, audit and financial variables in a logit model. The model is able to identify distress prior to the GFC successfully. Tatom and Houston (2011) applied the CAMEL system using the DEA approach to the GFC (2006-10) and the savings & loans crisis (1988-94). This model was able to predict the failures in both crisis periods accurately. Avkiran and Cai (2012) also employed a DEA model with a fully specified CAMELS model. They included financial market information such as credit rating and were able to identify distressed banks up to two years ahead. Although the extent of the CAMEL categories used varies, the findings suggest that identification of bank distress in the GFC crisis was possible.

As far as we know, there is no study that incorporates bank distress for non-crisis and crisis periods over a long and continuous time span. It is inherently difficult to study periods of little distress and few failures, studies therefore miss potential misjudgements or false alarm in stressful non-crises times by not including these non-distressing periods. Our study tackles and tries to fill these gaps, particularly by including later phases of the GFC. We search for stable systemic patterns in the CAMELS variables over a long time period in the US banking market from 1992 to 2011. For this purpose we employ both the logit estimation technique and survival time analysis. These statistical approaches are most appropriate to deal with models that cover many time periods, a large number of financial institutions and a wide range of explanatory variables. In the period we cover there have been various financial distortions and shocks and our model has to capture variation in triggers of bank distress and identify time-consistent indicators to gauge bank distress.

2 Data

This paper utilizes reports from the FDIC statistics on depository institutions (SDI). These data cover only FDIC insured institutions. The raw data set covers all insured financial institutions operating between the last quarter of 1992 and the second quarter of 2012. The data are publically available and are on a quarterly basis, providing 710,217 observations on 16,188 banks. The number of institutions is not constant over the period due to market entry and exits. As shown in Table 2, the banks have one of four principal supervisors: Federal Reserve Board (FRB), Office of the Comptroller of the Currency (OCC), Office of Thrift Supervision (OTS) and the FDIC[28]. The database distinguishes five categories of bank, which are labelled in Table 2. All insured depository institutions are members of the FDIC's Deposit Insurance Fund (DIF).

Since we are interested in explaining and predicting bank distress and bank failures, the dependent variable in our model is binary. If a bank fails or get into distress, the value of the variable will be 1 and otherwise 0. The characterisation whether of a bank is assessed as distressed or failed is obtained from the public FDIC institution directory. Over the data period, 541 institutions can be identified as troubled. To be considered as troubled the financial institution must be either receiving assistance by a transaction from the FDIC or facing some kind of distress or failure in the time period. Of the 579, 566 were banking failures and 13 banks got into distress and received assistance from the FDIC. Unfortunately, the FDIC does not always provide the data for the troubled period, so that we are constrained to use the last available data period to model the difficulty of the bank. Therefore, there may be a divergence between the official FDIC failure date and the failure date we use. In addition, we also have to drop 26 failures from the sample that do not have sufficient available data points for the troubled period, leaving us with 553 events of bank distresses - 543 bank failures and 10 banks that have received assistance.[29]

Most banks are supervised by the FDIC (Table 3) and the largest bank type is commercial banks. Most failures occurred in FDIC supervised banks and predominantly in commercial banks with a

[28] The Office of Thrift Supervision was dissolved and merged with the Office of the Comptroller of the Currency in July 2011.

[29] De novo banks have not been removed from the sample, although DeYoung (2003) proposes this as he finds that new banks have a bias and distort results. We explore this possibility in Section 5 but omission has little impact so we leave de novo banks in the sample.

higher proportion in these two categories than in the relative distribution of banks. Just 3.24% of the all FDIC regulated banks got into trouble. The slightly higher proportion of failures among FDIC supervised banks is probably mainly a function of the size as failure rates among small and newer banks tend to be the largest (DeYoung, 2003).

The total number of banks decreased steadily over the sample period (Figure 1). This reflects consolidation within the financial sector as well as the changing regulatory framework. There are two spikes in the number of distressed or failed banks. The first, in 1993, indicates the last consequences of the savings & loan crisis, whereas the second, from its beginning of 2008 to the end of the sample data, reflects the global financial crisis. While bank failure or distress occurs predominantly in phases of banking or financial crisis, there are non-crisis examples.

We use a single variable to represent each of the individual C, A, M, E, L and S categories. The detailed definitions and the expected signs of their impact are given in Table 4.

We incorporate the *capital adequacy* in three ways: leverage ratio, risk-based capital ratio, and gross revenue ratio.[30] For the risk-based capital ratio we use the total capital ratio which is adopted in Basel II/III. The non-risk-weighted leverage ratio is total equity minus estimated losses to assets. The gross revenue ratio is tier 1 capital to total interest and noninterest income. We incorporate only one indicator at a time as they are substantially substitutes empirically. For all capital indicators we assume a negative relationship to banking failure; the lower the capital adequacy, the more likely is a failure. To estimate *asset quality* we use the ratio of nonperforming loans to total. We anticipate a positive relationship with banking failure, the larger the proportion of non-performing loans, the more likely is a failure. For *management competence and expertise* of banks we use the efficiency ratio provided by the FDIC. It measures the proportion of net operating revenues that are absorbed by overhead expenses and a lower value indicates greater efficiency. Therefore, we assume a positive relationship; the higher the ratio, the more likely is a failure.

We follow the trend of using the net operating income to assets ratio to capture the *earning ability and strength* of the banks and assume a negative relationship with banking. The lower the earnings, the more likely is a failure. For *liquidity* we use the loan-to-deposit ratio to capture this effect as no direct liquidity measures are available. A high LTD ratio may indicate the lack of liquidity and possible repayment problems for sudden unforeseen obligations. We expect a positive sign for

[30] The definition of the variables is based on Estrella, Park, and Peristiani (2000).

the liquidity indicator. It is difficult to find an adequate indicator for the *sensitivity to market risks*, since different banking businesses have varying degrees of market engagement. We measure the sensitivity as the bank's dependence on volatile liabilities; sometimes this ratio is also used to measure liquidity (Curry, Fissel, & Elmer, 2003). The ratio is calculated as total volatile liabilities divided by total assets. We expect a positive sign for the sensitivity indicator

All explanatory variables have been winsorized[31] at the 1% level separately for crisis and non-crisis events to remove data errors and anomalies. The observations of banking failures and distress events have been excluded from this process, since we assume that they are tail events and hence would be removed from the sample.

Banks' characteristics alone may be insufficient to determine failure as the phase of the economic cycle may have an impact. Failure is more likely in unfavourable conditions.[32] Therefore, we include *real gross domestic product* (GDP) to capture this, as in Männasoo and Mayes (2005, 2009). It is measured as the seasonally adjusted percentage change from preceding period in real gross domestic product based on the data from the Bureau of Economic Analysis (BEA). The expected sign of GDP is hence negative.

The mean values of variables for healthy banks and troubled banks are clearly different (Table 5). Since there are so few troubled banks the mean values of the total sample are very close to the ones in the healthy bank subsample. Not surprisingly, troubled banks have a lower mean in the categories of capital, management, earnings, and GDP in comparison to the healthy banks, but their mean values in the categories assets, liquidity, and sensitivity are higher, reflecting our expectation. The means for distressed banks are clearly higher, but have very large standard deviation. This may indicate that while the indicator is suitable for some distress events it may be less practicable for others. To lesser extent this might be true for the gross revenue ratio and liquidity indicator and may indicate difficulties in measuring these effects.

The CAMELS indicators are little correlated with each other (Table 6), so that this should limit any problems from multi-collinearity in estimation. There are two exceptions. The earnings variable is considerably negatively correlated with the indicators of assets and management and the liquidity variable is substantially positively correlated with the sensitivity indicator. The former correlation suggests that inferior asset quality is accompanied by weaker earnings. These

[31] For more information on winsorizing see for instance Barnett and Lewis (1994, p. pp.78ff.)

[32] In this paper we do not include any market information indicator such as bond spreads, CDS or VIX, as our sample mainly includes non-listed regional banks, which tend to re-finance themselves outside financial markets.

earnings also have a substantial influence to the efficiency ratio. The latter correlation indicates that the sensitivity to markets indictor is interrelated with liquidity, which is the case by definition.[33] In addition to the correlation matrix, we have also checked for suspicious variance inflation factors and find no abnormality. All factors are in the interval between 1 and 2. Therefore, the data do not seem to contain any serious correlation issues and we can use our estimation techniques. The capital adequacy indicators are substitutes and not used simultaneously. Nonetheless, the correlation suggests that the explanatory powers of the leverage and risk-based capital ratio might be close.

3 Results

It is worth noting some prima facie indicators that are clear from the data (Figure 2). Both the banks which ultimately failed and those that did not tended to run their capital adequacy down in the period up to the global financial crisis. While on average, those who ultimately failed tended to have around 5% less capital even in the best years, the gap widened from 1997. This illustrates that the fragility was being built up over a longer period rather than simply that losses were incurred in the global financial crisis to banks that had not otherwise shown signs of weakness. Since we aim to find robust indicators for detecting bank failures, we apply two different estimation techniques to satisfy this demand. Multivariate logit estimation is applied in a panel data environment as well as time survival analysis in the time dimension and hence on the time to default. We start by using the logit approach, conditioned on balance sheet and economic indicators for each bank to determine the best capital adequacy indicator from the model. The regression model has the following specification:

$$\mathrm{D_i} = \begin{cases} = 1 \text{ if bank i is distressed or fails} \\ = 0 \text{ otherwise} \end{cases} \tag{14}$$

$$\mathrm{D_{it}} = \mathrm{Cons} + \beta_C X_{C,it} + \beta_A X_{A,it} + \beta_M X_{M,it} + \beta_E X_{E,it} + \beta_L X_{L,it} + \beta_S X_{S,it} + \beta_{GDP} X_{GDP,t} \tag{15}$$

where the vector of explanatory variables X contains: capital adequacy C, asset quality A, management expertise M, earnings strength E, liquidity L and sensitivity to market risks S as well as GDP. In addition, we also incorporate a constant in our model to take account of other influences that are not reflected by our explanatory variables. Since we apply a random effects

[33] In fact, some researcher like Curry, Fissel, and Elmer (2003) use this ratio to capture liquidity aspects.

panel model, we estimated for each bank *i* in each period *t* the influence from the dependent variable.

The three columns of Table 7 contrast the results from using the three different capital adequacy measures: (1) the leverage ratio (LEV), (2) the risk-weighted capital ratio (RBC) and (3) the gross revenue ratio (GRR), respectively. The indicators in the first and second specifications have all the expected signs (Table 7) but there are some drawbacks. Model (2) and (3) fail to find a significant influence from the sensitivity variable on the distress of banks. The management variable has no significant influence to the distress of banks in the specification (2). This model also suggests that the inclusion of the constant may be irrelevant. For models (1) and (2) capital adequacy is the major driver in explaining of bank distress, but in model (3) the GRR ratio delivers only a minor but highly significant explanation. In all models, asset quality and earning ability are able to explain a considerable amount of the variation. Further, GDP has the expected clear effect. In an economic downturn the likelihood of a financial institution getting into distress is much higher than in good times. A lack of liquidity raises the vulnerability of banks in all models. Interestingly, the liquidity variable has very limited explanatory power. In addition to the insignificant parameter of management and sensitivity, model (3) also has high standard errors for many coefficients, which may indicate that this model is poorly specified. This is confirmed by the log likelihood ratio and information criteria. In total, there is little to choose between models (1) and (2).

Turning to the time survival analysis, we use Cox (1972) proportional hazard estimation. The Cox proportional hazard model incorporates the time dimension in the prediction and offers a further approach to testing for the best predictions. We use the same three possible specifications in a time survival analysis and employ the same explanatory variables as in the logit models. Again, the leverage ratio, the risk-weighted capital ratio and the gross revenue ratio form three competing specifications labelled (1), (2) and (3).

It is immediately clear from Table 8 that these models do not explain behaviour in as well determined a manner as the logit model. Except for GDP and sensitivity, the coefficients have the expected signs. Nevertheless, the coefficients for management, sensitivity and the GDP indicator are not or only barely significant. Unlike the logit model, all three models show a clear and similar influence from capital adequacy, assets and liquidity. As before capital adequacy and then the amount of non-performing loans (asset quality) showed the most important influence on bank distress. Although earnings are generally less important in the time survival, they have a substantial influence on the likelihood of insolvency. Again there is little to choose between models (1) and (2), although the individual coefficients are somewhat better determined.

Taken together, we get similar results to other authors. Capital adequacy, assets (non-performing loans), liquidity and earnings have a clearly distinguishable influence on bank distress. Management and sensitivity seem to be less important. Less clear, rather surprisingly is the general influence of economic conditions. There is little to distinguish performance of the leverage ratio from the commonly used risk-based capital ratio as a capital adequacy indicator. However, what is notable is that, in contrast to Estrella, Park, and Peristiani (2000), the GRR does not seem to be so useful.

4 Prediction Accuracy and Forecasting Ability

Previous literature warns that bank distress and failure are difficult to predict (Worrell, 2004), so we assess the in-sample and out-of-sample predictive power for both estimation techniques. For the logit model we use the linear prediction technique with a cut-off point at 50%. All predictions with a value over 50% are considered as indicating failures. For the time survival analysis we employ Harrell's concordance coefficient to assess the predictive quality of the different models. [34] The in-sample prediction accuracy is shown in Table 9.

Before interpreting the results it is worth nothing the accuracy of the estimation techniques cannot be directly compared, because the techniques are based on different assumptions. Nonetheless, some inferences can be drawn. First of all, none of the models falsely detect banking failures, so there are no type II errors. Again the leverage ratio and risk-based capital measures show similar performance. With the logit technique we can classify 80% of all distress and failure events of financial institutions correctly and with the time survival model about 97%.[35] In contrast, the forecasting ability of the gross revenue ratio logit model is clearly worse.

However, these findings relate to in-sample predictions where accuracy is expected to be good. To mimic real life, where one has no knowledge of the events to come we re-estimate the models from 1990s only up to the beginning of the GFC and make predictions about failures

[34] Harrell's 'C' concordance coefficient was proposed and developed by Frank E. Harrell Jr., Califf, Pryor, Lee, and Rosati (1982), and Frank E. Harrell Jr., Lee, and Mark (1996).
[35] We have also checked for different cut-off points. The results are in line with our findings. However, for example for the logit model, the accuracy declines at the 75% and 90% cut-off points to 72% and 65%, respectively.

during the GFC to give out-of-sample forecasts.[36] We only show results for the leverage ratio as these were the more robust. This sub-sample (Q4/1992-Q2/2007) covers 113 in sample failure events of which can predict 74 (65%). We use these estimates to predict the 443 failures during the GFC. We are able to predict 83% (368) of these failures. This suggests that the causes of failures in the GFC are not different from previous failures and that despite any differences in the individual coefficients from using the shorter data period, their predictive ability remains good.

We take this approach further by seeing how progressive out-of-sample prediction ability would have been if each year the model was re-estimated to take all the available data into account[37]. We are in effect applying a rolling regression, although the starting date remains fixed. First, we estimate from 1992 to 2005 and then predict all remaining failures. We then roll the end date of the panel forward a year at a time to 2010 and predict the remaining failures on each. The predictive accuracy of different windows is shown in Table 10. The quality of the in-sample predictions remains stable, improving somewhat when 2010 is added, suggesting that the explanatory power is not only driven by the failures in the global financial crisis. Out-of-sample prediction ability remains good throughout, not surprisingly rising as the prediction period shortens.

Additionally, we investigate the development and the relation of the regression coefficients in the GFC. Figure 3 shows the development of the estimates from 24 rolling regressions from 2005Q1 to 2010Q4.[38] Not surprisingly because we quickly add far more failures than we had in the pre-GFC data set, the coefficients start changing, quite substantial for some of the poorly determined estimates From 2008 to 2009 the capital indicator coefficient falls by nearly a quarter of its value before rising again to within 10% of its pre-GFC value. This pattern is accompanied by an increasing asset quality and declining earnings coefficients as the GFC takes hold. However, in the latter case the change is more than reversed by the end of the period. These paths as well as the spike in the liquidity indicator coefficient (liquidity squeeze) reflect characteristics of the global financial crisis. But, capital, earnings and liquidity, remain the main drivers. Although the ranking of their relative importance does not vary, their magnitude does, reflecting the features of the newly incorporated failures.

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[36] The regression results with the logit model are similar to those with the full sample; only the sensitivity and GDP coefficients are insignificant.
[37] Clearly the model can be re-estimated each quarter as we do below but we only illustrate annual steps here.
[38] The coefficients for management, sensitivity, and GDP are sometimes insignificant.

In common with many other EWS models but unlike Männasoo and Mayes (2005, 2009), we have up to this point been using models that 'explain' failures in terms of the CAMELS indicators. We turn to the forecasting ability of the logit model and forecast the dependent variable up to four quarters ahead ($t_{+1} \to t_{+4}$) only using the information at t_0. We forecast failures for all three logit specifications (Table 11) with two different thresholds (25% and 50%) for the probability of a failure. The leverage ratio and risk-weighted specifications have very similar success rates in forecasting distress over all horizons and probabilities. Both models can nearly explain 80% of the failures one and two periods ahead. The GRR model lags behind with 59% and detects one 'false' failure. That confirms the findings of Section 3 that the GRR is not the best specified model. The forecasting ability three quarters and four quarters ahead is much worse in every instance. At three and four quarters ahead it is only possible to forecast about one failure in seven with the 50% threshold. At the same the number of forecasts of failures that did not happen also rises to around 10% of the total number of failures. The marked decline is expected, since the indicators are based on balance sheets figures. The further ahead the forecasted period, the lower is the prediction quality and the higher are the forecasting errors. At the 25% threshold for the first two periods the forecasting ability is a little better than with the 50% thresholds. The three and four quarter ahead forecasts are not surprisingly a little better at one in five failures but this is at the expense of falsely identified failures rising to the same level.

These results confirm what many supervisors find that failures are very difficult to forecast more than six months ahead but they are much easier to detect within that horizon. Hence a well-designed EWS (on the basis of the US data) could provide the necessary warning time to put all the measures in place needed for an orderly failure. It is also clear that the simple leverage ratio forms just as well as the more sophisticated risk-weighted measures, so there is no predictive gain from the complexity.

5 Test of Robustness

It is possible that we have omitted other characteristics of banks that contribute to their failure or its avoidance. Such omissions could both reduce potential predictive performance and bias the included coefficient estimates. We therefore test for the presence of six further possible explanatory variables, both individually and jointly. These are as follows:

- model (2) incorporates the size of the institution,
- model (3) includes the age of the business,

- model (4) considers the effects of ownership type,
- model (5) takes into account whether the institution is part of a holding company,
- model (6) tackles the wide-spread impression that the GFC was different,
- model (7) considers whether failure rates are affected by who the supervisor is, and finally
- model (8) contains a parsimonious specification of all of the above possibilities.

The results are shown in Table 12.

We use the leverage ratio logit model, *model (1)*, as the base for these tests In the re-estimation, the coefficients of the explanatory variables (CAMELS & GDP), vary somewhat but have the expected signs and are significant.

As a first step, we consider bank size, measured as the log of assets as a possible influence.[39] Smaller banks are more likely to fail, because bigger institutions tend to be more diversified and in some more likely to be treated favourably because of the adverse consequences of their failure. We hence expect a negative sign. However, our sample does not confirm this hypothesis, the sign is positive and the variable is insignificant. There is a second reason for expecting that size may be important. Hau, Langfield, and Marques-Ibanez (2012) suggest that rating agencies systematically underestimate the relative risks of larger banks, in part because they feel they are too big to fail but also because those banks can exert disproportionate influence on the raters. While we use what are apparently unbiased measures of the state of the bank, it is possible that the authorities may not react unambiguously to the sign of fragility irrespective of size of the bank.

Second, we test the hypothesis that the age of banks might have an influence on their likelihood of distress. The rationale is that de novo banks[40] might have an incentive to run their banks at low margins to gain a foot in the market or many simple take greater risk, revealed in CAMELS (DeYoung, 2003). Therefore, younger banks might be more fragile. Again the data do not support this hypothesis. Business age has no significant influence on the probability of failure.

Although the business age has no additional explanatory power, it might be interesting to investigate whether the characteristics of distressed de novo banks differ from established

[39] The size dummy has also been winsorized to be consistent with the CAMELS indicators.

[40] We retain the definition of the Federal Reserve System (FED) (1991) that a de novo bank is a bank that "has been in operation of five years or less".

distressed banks. We break down our sample into de novo banks and established banks with 49 and 507 failures, respectively. The results are given in Table 13. Perhaps the most interesting consequence is that the CAMELS model becomes much better determined. All six elements (and GDP) have the correct signs and are significant at least the 5% level.[41] This implies that de novo banks are fogging the results by being much less easily explained. De novo bank failures appear to have just two indicators with any substantial significance. Capital has the strongest influence, interestingly enough with a very similar coefficient to the rest of bank failures, while earnings are also important.. These indicators reflect the challenges of young banks. Their business model tends to be riskier and has a lower profitability than established banks.[42]

Thirdly, there are two ways in which the form of ownership might have an influence on fragility. First of all, joint stock banks may be more likely to fail than mutual institutions, if, for example, they are engaged in riskier business activities. We there insert a dummy variable to distinguish joint stock banks from mutual institutions (labelled ownership in Table 12). Our data suggest that this relationship may hold and joint stock institutions do indeed have a greater likelihood of failure.

However, there is a second aspect of ownership that is prima facie also important. Banks are often owned by bank holding companies and this can be expected to decrease their chance of failure as the holding company can act as a source of strength. The affiliation to a holding company may have also benefits for the individual banks because of access to better diversification or better funding opportunities. Furthermore the opportunity to acquire better operating systems and management practices should be greater. We would therefore expect a negative coefficient. Our data offer no support for this.

We also consider whether the global financial crisis from Q3/2007 onwards differs from the rest of the dataset and whether it reflects unusual behaviour as there were so many failures in this period. Again, our model offers no support for this hypothesis and suggests that the GFC is not different from other periods. This corroborates the findings in Section 4. We try varying the date for the onset of the crisis but do not find a clear break point. We tried interacting this GFC

[41] The most notable effect is that the indicator for sensitivity to market risk is for established banks is now clearly significant. Therefore, the insignificance of the total sample seems to be due to the presence of de novo banks, where the sign of the sensitivity coefficient is opposite.

[42] Dividing the sample leads to a small improvement in predictive accuracy. Whereas the full sample leverage logit model classified 80% of all distress and failure events of financial institutions correctly, the sub-samples of de novo banks and established banks classify 90% and 80% of the events correctly, respectively.

dummy with the other coefficients in the model in order to test whether any change in behavior was more comprehensive. Interestingly enough only two variables showed a change in effect: Earnings and Sensitivity, in both cases failures became more responsive to changes in these variables. Sensitivity was rather poorly determined in the sample as a whole and including these shift coefficients clearly helps.

Lastly, the regulatory framework might have an effect. It is not just that regulators may behave differently but they regulate also different sorts of bank. Some types of banks may be more exposed to failure than others (Table 3). There is some suggestion of regulatory competition with some regulators pursuing a more laissez-faire approach to gain competitive advantage (Mayes, Nieto, & Wall, 2011). FDIC regulated banks reflect the base scenario. Our data suggest that non-FDIC regulated banks are more likely to get into distress. FDIC-regulated banks are less exposed to insolvency than banks supervised by the FED, OCC or OTS. OCC-regulated commercial banks are significantly more likely to get into distress. At this stage the explanation is rather speculative. OTS supervised institutions tend to be more exposed to the property sector but involved in a more conversation range of lending. Hence lighter supervision but exposure to extreme events might be rational. The OCC results are more difficult to explain as those are larger banks.

We therefore investigate the influence of regulatory bodies and different capital measures to banking distress further, by running logit regressions for each regulatory type separately (Table 14) and examining their forecasting abilities (Table 15). The results suggest that the leverage ratio is more helpful for FRB-supervised banks. The risk-based capital model is more useful for FDIC and OCC-supervised banks. A rationale might be that FRB-supervised banks (bank holdings companies) are more complex than commercial banks and the leverage ratio is more adequate for complex banks. This would bear out the comments of Haldane and Madouros (2012) that it is the supervision of complex institutions that would benefit most from simpler indicators. The risk-based capital seems to be more striking for commercial banks. The tables also reveal that OTS-supervised banks seem to be different.

Finally, we include all of the extra significant influence categories (ownership and supervisor type) in *model (8)*. The base scenario represents FDIC supervised non-stock banks. All the variables still have the expected sign and the significance of the individual parameters remains similar, however the management variable is only significant at the 10% level. OCC supervision may be a proxy for size, since our continuous measure does not capture this this simple division - but is still the counter-intuitive sign.

These tests therefore suggest that we have a quite a robust and stable formulation for the CAMELS model, although it is the capital adequacy variable that is the main and resilient driver. Omitting the AMELS variables still gives good predictability, as also noted by Haldane and Madouros (2012). The goodness of fit and prediction accuracy for *model (8)* are similar to *model (1)*, implying that this base model offers a reasonable explanation as it stands.

6 Conclusion and Policy Implications

In this paper we apply the well-established CAMELS method to predict bank distress for the last 20 years in the US. We find that all the traditional CAMELS factors used in previously are robust and stable while explaining recent banking failures accurately. Concentration just on capital adequacy, for example, while capturing most occurrences, would miss many of the problem cases. Further, we investigate which traditional indicators are more efficient in predicting distress and failure In exploring the appropriate measurement of capital we find that risk-weighted measures do not outperform a simple leverage ratio.[43] This does not imply that there should be any reduction in the use of risk-weighted measures in deciding how much capital a bank should hold in normal times but that when things start to go wrong, a simple leverage ratio, which is transparent and more difficult to manipulate, would be the better indicator of problems.[44] We look for a range of possible improvements to the basic CAMELS formulation but find just two to have any noticeable effect. The failure characteristics of de novo banks seemed to be somewhat different and can be explained by just two factors (capital adequacy and earning power). Additional parameters do not offer any further explanation. Further, we investigate the predictive quality of our model and find that the logit leverage specification performs well in forecasting bank distress up to two periods ahead.

The evidence in this paper suggests the traditional types of early warning model of bank distress available before the global financial crisis would have worked quite well during the crisis. Although the parameters of the models do change when the much larger number of failures during the GFC are added to the data set and the forecasting ability of the models improves, these improvements are relatively small.

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[43] When a shorter sample period is used the leverage ratio tends to perform a little better.

[44] Blum (2007)shows in a simple model why having a leverage ratio requirement in addition to risk-sensitive requirements increases social welfare if the costs of bank failure and the fraction of risky banks is high and the cost of capital low.

As a result we conclude that Basel III is correct in including the leverage ratio in its requirements for improved supervision and that supervisors would be wise to adopt it. It is of course possible that the US is unusual in this regard and future work needs to be undertaken elsewhere – on European data for example – to make sure that it is reasonable to apply the implications elsewhere. However, on the basis of our estimates, if anything, it might be that higher prominence is warranted for the leverage ratio in the Basel framework and perhaps the trigger value should be somewhat harsher. At the present it is likely to act rather more as a backstop to the risk-weighted measures. If we follow the reasoning of Haldane and Madouros (2012) then the leverage ratio would be the preferred indicator when crisis threatens.[45] No doubt other estimation methods could be used, such as data envelopment analysis but our results seem sufficiently clear that we would not expect them to be totally overturned.

[45] This point is made in a different way by Demirguc-Kunt, Detragiache, and Merrouche (2010), when they conclude on the basis of an unbalanced sample of 381 large banks from 12 countries that 'during the crisis stock returns of large and under-capitalized banks were much more sensitive to leverage ratios as opposed to risk-adjusted capital ratios. This may be because market participants viewed risk-adjusted ratios as much less transparent.'

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Appendix

Figure 1: Number of Banks over Time

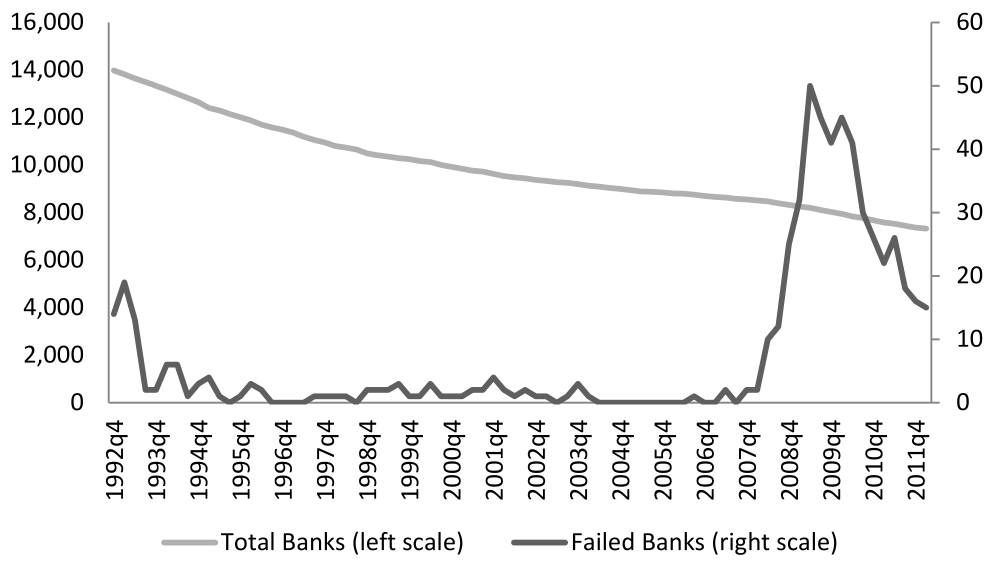

Figure 2: Ratio of Risk-weighted Assets to Total Assets

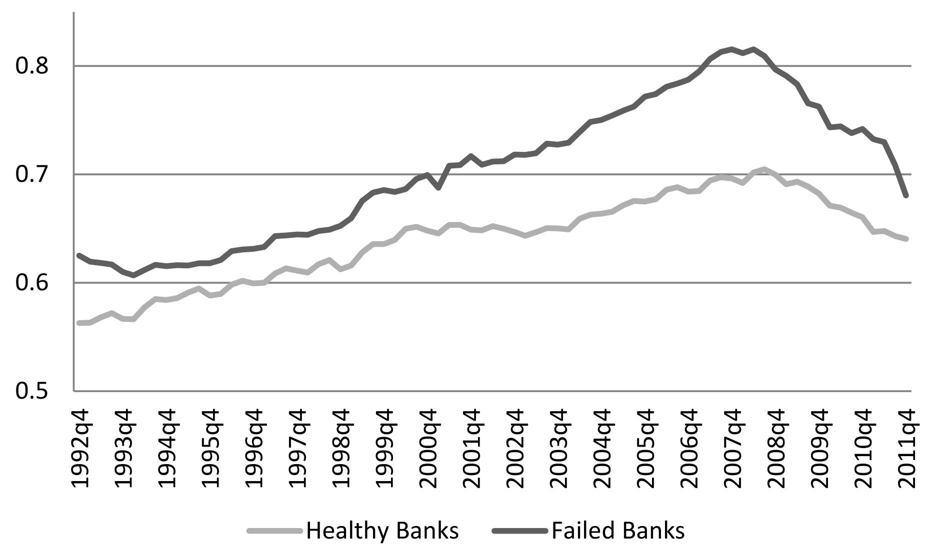

Figure 3: Stability of Coefficients

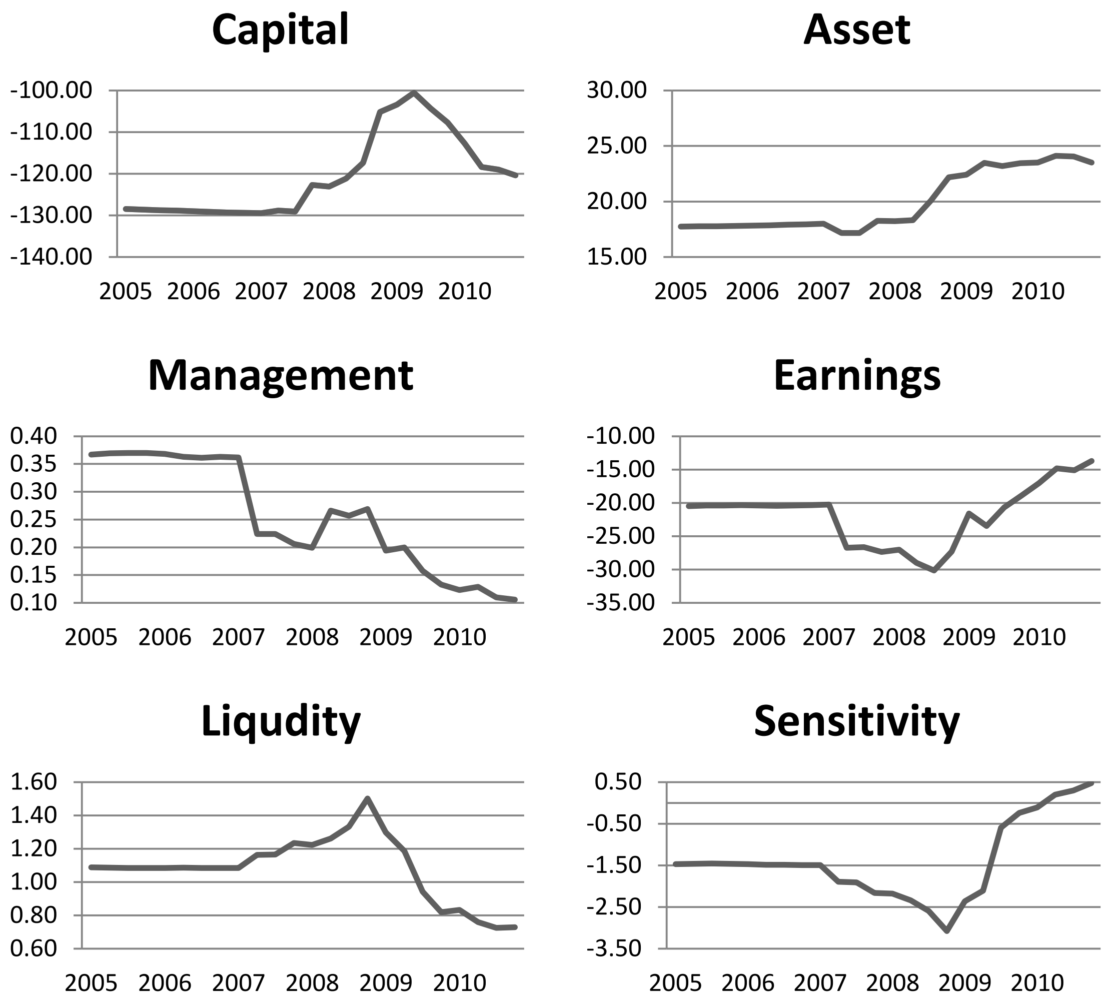

Table 1: Meta-Analysis and Overview of Important Banking-Failure Literature

Study	Methods					Variables Used								
	Model (compared)	Period	Banks (Distressed /Failed)	Region	Accuracy	Total	Used	C	A	M	E	L	S	Others/Remarks
Meyer and Pifer (1970)	MDA	1948-65		USA	~80%	160	32							balance sheet ratios and growth rates
Sinkey (1975)	MDA	1969-72	222 (111)	USA	~75%	100	7	X	X	X	X	X		
Altman (1977)	MDA	1966-73	212 (65)	USA	~90%	32	12	X	X		X			
Martin (1977)	LOGIT	1970-76	5642 (58)	USA	~88%	25	4	X	X		X			residual proxy for loan risk, illiquidity, and management strategy
Hanweck (1977)	PROBIT	1973-75	177 (32)	USA	~67%	-	6	X	X		X			
Avery and Hanweck (1984)	LOGIT	1979-83	1190 (100)	USA	~	9	7	X	X		X			
Barth, Brumbaugh, Sauerhaft, and Wang (1985)	LOGIT	1981-84	906 (318)	USA	~80%	12	6	X	X		X	X		
Lane, Looney, and Wansley (1986)	HAZARD	1979-84	464 (130)	USA	~85%	21	7	X	X		X	X		
Pantalone and Platt (1987)	LOGIT	1983-84	216 (113)	USA	~86%	-	5	X	X		X			
Abrams and Huang (1987)	PROBIT	1977-84	14440 (195)	USA	-	15	4	X	X		X		X	size
Tam and Kiang (1990, 1992)	ANN (LOGIT, MDA)	1985-87	118 (59)	Texas	ANN> LOGIT, MDA	19	19	X	X		X	X		
Thomson (1991)	LOGIT	1984-89	1736 (770)	USA	93%	16	16	X	X	X	X	X		
Whalen (1991)	HAZARD	1987 -90	1500 (500)	USA	80-90%	11	5	X	X		X		X	
Salchenberger, Cinar, and Lash (1992)	ANN (LOGIT)	1986-87	200 (100)	USA	ANN > LOGIT	29	5	X	X	X	X	X		
Berg and Hexeberg (1994)	LOGIT	1988-93	150 (25)	Norway	-	11	11	X	X	X	X			

Study	Methods					Variables Used								
	Model (compared)	**Period**	**Banks (Distressed /Failed)**	**Region**	**Accuracy**	**Total**	**Used**	**C**	**A**	**M**	**E**	**L**	**S**	**Others/Remarks**
Barr and Siems (1994)	DEA	1986-88	739 (294)	USA	90%	6	6	X	X	X	X			
Cole and Gunther (1995b)	HAZARD	1985-92	10843 (811)	USA	-	19	14	X	X		X	X		managerial decision-making efficiency, bank structure, and economic conditions
Henebry (1997)	HAZARD	1985-89	~850	USA	-~95%	29	-	X	X	X	X	X		different data sets and model periods, various variables for cash flow ratios
Alam, Booth, Lee, and Thordarson (2000)	ANN	1985-92	(1200)	USA	-	25	8	X	X		X			
Estrella, Park, and Peristiani (2000)	LOGIT	1988-92	13299 (600)	USA	95%	3		X						as risk-based capital measure, leverage ratio and gross revenue ratio
Wheelock and Wilson (2000)	HAZARD	1984-93	4022 (282)	USA	-	14	10	X	X	X	X	X	X	miscellaneous factors: like size, holding company affiliation, branching, and age
Logan (2001)	LOGIT	1991-94	540 (84)	UK	~70%	15	4	X	X		X	X		
Swicegood and Clark (2001)	ANN (MDA, judgment)	1980s-90s	1741 (384)	USA	ANN > judgment> MDA	20	20	X	X		X	X		non-financial bank characteristics
Kolari, Glennon, Shin, and Caputo (2002)	ANN (LOGIT)	1989-92	1000 (55)	USA	100% vs. 96	28	28	X	X		X	X	X	diversification , size
Bongini, Laeven, and Majnoni (2002)	LOGIT	1996-98	246	East Asia	83%	7		X	X	X	X	X		credit ratings, and stock market prices
Curry, Fissel, and Elmer (2003)	LOGIT	1988-95	200	USA	95%	16	16	X	X	X	X	X		market and financial variables
DeYoung (2003)	HAZARD, LOGIT	1980-85	2371	USA	-	15	15	X	X	X	X	X		further bank characteristics
Kao and Liu (2004)	DEA	2000	24	Taiwan	-	7			X	X	X	X		financial forecasts and presents prediction in terms of efficiency scores
Tung, Quek, and Cheng (2004)	ANN	1980 - 2000	3635 (702)	USA	-	9	9	X	X	X	X	X		miscellaneous aspects

Study	Methods					Variables Used								
	Model (compared)	Period	Banks (Distressed /Failed)	Region	Accuracy	Total	Used	C	A	M	E	L	S	Others/Remarks
Männasoo and Mayes (2005)	LOGIT	1996-2003	200 (40)	Eastern Europe	~90%	10	10	X	X		X	X	X	macroeconomic and structural level
Halling and Hayden (2006)	LOGIT	1995-2002	150	Austria	65%	50	50	X	X	X	X			other risks and macroeconomics aspects, bank characteristics
Kraft and Galac (2007)	LOGIT	1996-2003	40 (17)	Croatia	~80%	10	7	X	X	X	X	X		deposit interest rates and risk-taking of the banks
Andersen (2008)	LOGIT	2000-05	136 (8)	Sweden	-	27	27	X	X	X	X	X		
Arena (2008)	HAZARD	1997-99, 1994-96, 1994-95	632 (135)	East Asia, Argentina & México, Venezuela	~50-60%	14	9	X	X	X	X	X		interest rates, bank characteristics, macroeconomic variables
Männasoo and Mayes (2009)	HAZARD	1995-2004	600 (188)	Eastern Europe	~90%	23	23	X	X		X	X	X	macroeconomic and structural indictors
Poghosyan and Cihák (2009)	LOGIT	1996 - 2008	5708 (79)	Europe	~70%	11	11	X	X	X	X	X		market discipline
Jordan, Rice, Sanchez, Walker, and Wort (2010)	MDA	2007-10	500 (225)	USA	88.2%	9	9	X	X		X			institutional characteristic variables
Jin, Kanagaretnam, and Lobo (2011)	LOGIT	2007-10	6437 (1248)	USA	~73%	12	10	X	X					accounting, audit quality and financial variables
Tatom and Houston (2011)	DEA (LOGIT)	1988-94, 2006-10	1470	USA	DEA> LOGIT	8 (10)	8 (10)	X	X	X	X	X		economic conditions
Avkiran and Cai (2012)	DEA	2004-09	186 (31)	USA	-	9		X	X	X	X	X	X	financial market information such as credit ratings
Cole and White (2012)	LOGIT	2004-08	7146 (263)	USA	~95%	14	14	X	X	X	X	X		

Table 2: Bank & Regulator Types

Banks Types		Supervisor	
Abbr.	**Description**	**Abbr.**	**Description**
N	commercial bank, national (federal) charter and Fed member, supervised by the OCC	FDIC	Federal Deposit Insurance Corporation
NM	commercial bank, state charter and Fed non-member, supervised by the FDIC	FRB	Federal Reserve Board
SA	savings associations, state or federal charter, supervised by the OTS	OCC	Office of the Comptroller of the Currency
SB	savings banks, state charter, supervised by the FDIC	OTS	Office of Thrift Supervision
SM	commercial bank, state charter and Fed member, supervised by the FRB		

Table 3: Allocation of Banks and Supervisor

	Supervisor				Banks				
	FDIC	FRB	OCC	OTS	N	NM	SA	SB	SM
Banks (16,186)	51.50%	10.78%	25.97%	11.75%	23.66%	48.44%	12.14%	4.64%	11.13%
Failed Bank (530)	56.96%	10.13%	20.98%	11.93%	19.89%	54.61%	13.02%	2.35%	10.13%
Failures	3.24%	2.75%	2.37%	2.97%	2.54%	3.41%	3.24%	1.53%	2.75%

Table 4: Variable Definitions

Variables	Definition	Influence	Source
Capital (LEV)	Leverage Ratio: Total Equity minus Estimated Losses to Assets	-	FDIC
Capital (RBC)	Risk-Weighted Capital Ratio: Total Risk-Based Capital Ratio	-	FDIC
Capital (GRR)	Gross Revenue Ratio: Tier 1 Capital to Total Interest and Noninterest Income	-	FDIC
Assets	Nonperforming Loans (Noncurrent Assets plus Other Real Estate Owned to Assets)	+	FDIC
Management	Efficiency Ratio	+	FDIC
Earnings	Net Operating Income to Assets	-	FDIC
Liquidity	Net Loans and Leases to Deposits	+	FDIC
Sensitivity	Volatile Liabilities to Assets	+	FDIC
GDP	Seasonally Adjusted Percentage Change from Preceding Period in Real Gross Domestic Product	-	BEA

Table 5: Descriptive Statistics

Variable Name	Total Sample (N=710217)		Healthy Banks (N=709664)		Distressed Banks (N=553)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Capital (LEV)	0.0940	0.0368	0.0940	0.0366	-0.0129	0.0483
Capital (RBC)	0.1004	0.0356	0.1004	0.0356	0.0161	0.0356
Capital (GRR)	3.1759	2.4788	3.1778	2.4780	0.7339	2.3386
Assets	0.0119	0.0170	0.0118	0.0163	0.1555	0.0944
Management	0.6704	0.3677	0.6691	0.1916	2.3771	11.1306
Earnings	0.0094	0.0095	0.0094	0.0091	-0.0622	0.0649
Liquidity	0.8895	0.3713	0.8892	0.3429	1.2536	5.1004
Sensitivity	0.1458	0.1014	0.1458	0.1014	0.1671	0.1436
GDP	0.0269	0.0254	0.0269	0.0254	0.0118	0.0322

Table 6: Correlation Matrix

Variable Name	Capital (LEV)	Capital (RBC)	Capital (GRR)	Assets	Manage-ment	Earnings	Liquidity	Sensitivity	GDP
Capital (LEV)	1.0000								
Capital (RBC)	0.9304	1.0000							
Capital (GRR)	0.4840	0.4288	1.0000						
Assets	-0.1155	-0.0626	0.0102	1.0000					
Management	-0.1151	-0.1049	0.0330	0.3406	1.0000				
Earnings	0.1343	0.1412	-0.0581	-0.4383	-0.7650	1.0000			
Liquidity	-0.0128	0.0069	-0.0669	0.0919	-0.0157	-0.0370	1.0000		
Sensitivity	-0.0911	-0.0904	-0.0858	-0.0288	0.0050	-0.0583	0.6630	1.0000	
GDP	-0.0361	-0.0231	-0.1936	-0.1162	-0.1043	0.1165	-0.1277	-0.1014	1.0000

Table 7: Logit Models with Different Capital Adequacy Measures

Indicators	Model (1)	Model (2)	Model (3)
Capital (LEV)	-127.7*** (-22.96)		
Capital (RBC)		-148.4*** (-23.55)	
Capital (GRR)			-0.830*** (-11.24)
Assets	22.89*** (9.40)	28.52*** (11.84)	51.71*** (25.56)
Management	0.104** (1.98)	0.0543 (0.53)	0.141*** (3.57)
Earnings	-13.27*** (-3.51)	-14.43*** (-3.45)	-47.36*** (-15.96)
Liquidity	0.682*** (4.14)	1.034*** (3.56)	0.593*** (2.73)
Sensitivity	1.211* (1.80)	0.186 (0.22)	-0.400 (-0.66)
GDP	-12.40*** (-5.53)	-13.05*** (-5.54)	-7.312*** (-4.19)
Constant	-2.739*** (-7.41)	-0.253 (-0.52)	-9.446*** (-32.65)
Total Observations	710217	710217	710217
# of Bank Failures	553	553	553
Log Likelihood	-792.8	-784.3	-1251.8
AIC	1603.6	1586.5	2521.7
BIC	1706.9	1689.8	2625.0

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Time Surviving Analyses with Different Capital Adequacy Measures

	Model (1)	Model (2)	Model (3)
Capital (LEV)	-124.3*** (-22.70)		
Capital (RBC)		-147.4*** (-23.18)	
Capital (GRR)			-1.052*** (-17.04)
Asset	24.78*** (9.49)	31.49*** (11.40)	50.54*** (22.92)
Management	0.114* (2.23)	0.0727 (0.63)	0.127** (3.19)
Earnings	-8.553* (-2.25)	-9.087* (-2.07)	-41.67*** (-13.38)
Liquidity	0.708*** (4.89)	1.119*** (3.41)	0.391 (1.70)
Sensitivity	-0.410 (-0.51)	-1.669 (-1.53)	-0.0297 (-0.04)
GDP	44.81 (1.42)	45.14* (1.92)	1.286 (0.03)
Total Observations	710102	710102	710102
# of Bank Failures	553	553	553
Log Likelihood	-680.9	-667.9	-1055.5
AIC	1375.7	1349.8	2124.9
BIC	1456.0	1430.1	2205.2

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Prediction Accuracy

Capital Adequacy	Bank Distress	
	correctly detected	falsely detected
Logit Model		
Leverage Ratio	80.11%	
Risk-Based Capital	79.93%	
Gross Revenue Ratio	58.59%	
Hazard Model		
Leverage Ratio	97.10%	-
Risk-Based Capital	97.12%	-
Gross Revenue Ratio	96.62%	-

Table 10: Prediction Accuracy of Various Time Windows

Last Quarter of Estimation	In-Sample		Out-of Sample	
	Predicted Failure	# Failures	Predicted Failure	# Failures
Total Sample	80.22%	530	-	
2005Q4	66.96%	112	81.53%	444
2006Q4	67.86%	112	82.41%	444
2007Q4	65.52%	116	82.21%	440
2008Q4	61.82%	165	84.65%	391
2009Q4	70.95%	327	89.96%	229
2010Q4	76.62%	462	95.74%	94

Table 11: Forecasting Accuracy (Logit Models)

Logit Model *(50% Threshold)*	One Period Ahead		Two Periods Ahead		Three Periods Ahead		Four Periods Ahead	
	correctly detected	falsely detected	correctly detected	falsely detected	correctly detected	falsely detected	correctly detected	falsely detected
Leverage Ratio	80.11%	0.00%	15.17%	9.43%	13.88%	9.54%	14.63%	9.76%
Risk-Based Capital	79.93%	0.00%	14.55%	9.70%	13.51%	9.59%	14.48%	10.02%
Gross Revenue Ratio	58.63%	0.00%	14.71%	9.20%	13.67%	9.54%	14.86%	9.76%

Logit Model *(25% Threshold)*	One Period Ahead		Two Periods Ahead		Three Periods Ahead		Four Periods Ahead	
	correctly detected	falsely detected	correctly detected	falsely detected	correctly detected	falsely detected	correctly detected	falsely detected
Leverage Ratio	84.89%	0.00%	21.38%	16.09%	20.61%	15.40%	20.40%	15.74%
Risk-Based Capital	84.81%	0.00%	21.25%	16.17%	20.04%	15.47%	20.71%	16.26%
Gross Revenue Ratio	67.81%	0.72%	20.92%	16.09%	20.39%	15.40%	20.62%	15.74%

Table 12: Robustness Checks

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Capital (LEV)	-127.7*** (-22.96)	-127.5*** (-22.96)	-127.7*** (-22.87)	-127.6*** (-22.86)	-127.7*** (-22.94)	-127.7*** (-22.97)	-127.6*** (-22.91)	-127.2*** (-22.88)
Assets	22.89*** (9.40)	22.73*** (9.32)	23.55*** (9.51)	23.16*** (9.43)	22.90*** (9.40)	22.56*** (8.98)	23.59*** (9.52)	24.11*** (9.64)
Management	0.104** (1.98)	0.105** (2.06)	0.107** (2.07)	0.104* (1.93)	0.104** (1.97)	0.102* (1.93)	0.105** (2.04)	0.103* (1.89)
Earnings	-13.27*** (-3.51)	-13.98*** (-3.69)	-13.72*** (-3.61)	-13.66*** (-3.63)	-13.28*** (-3.51)	-13.03*** (-3.43)	-13.47*** (-3.52)	-13.97*** (-3.68)
Liquidity	0.682*** (4.14)	0.645*** (4.39)	0.684*** (4.03)	0.640*** (4.80)	0.683*** (4.12)	0.675*** (4.33)	0.691*** (3.51)	0.648*** (3.99)
Sensitivity	1.211* (1.80)	1.092* (1.66)	1.333* (1.94)	1.576** (2.38)	1.197* (1.75)	1.268* (1.89)	1.135 (1.50)	1.316* (1.83)
GDP	-12.40*** (-5.53)	-11.98*** (-5.27)	-12.16*** (-5.40)	-11.65*** (-5.13)	-12.45*** (-5.48)	-11.86*** (-4.78)	-12.92*** (-5.69)	-12.36*** (-5.40)
Size		0.0800 (1.39)						
Business Age			0.00391 (1.51)					
Ownership				1.186*** (2.56)				1.407*** (2.87)
Bank Holding					-0.0214 (-0.12)			
GFC						0.107 (0.51)		
Supervisor: FED							0.0885 (0.30)	0.0749 (0.25)
Supervisor: OCC							0.654*** (3.10)	0.657*** (3.12)
Supervisor: OTS							0.181 (0.75)	0.503** (2.01)
Constant	-2.739*** (-7.41)	-3.678*** (-4.78)	-3.001*** (-7.54)	-3.932*** (-6.69)	-2.726*** (-7.08)	-2.781*** (-7.39)	-2.975*** (-7.62)	-4.429*** (-7.04)
Total Obs.	710217	710217	710217	710217	710217	710217	710217	710217
# of Banks	16188	16188	16188	16188	16188	16188	16188	16188
Log Likelihood	-792.8	-791.9	-791.0	-788.5	-792.8	-792.7	-788.2	-783.0
AIC	1603.6	1603.7	1602.1	1597.0	1605.6	1605.4	1600.4	1592.0
BIC	1706.9	1718.4	1716.8	1711.7	1720.3	1720.1	1738.1	1741.1

Standardized beta coefficients; *t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: De Novo Banks

	All Banks	De Novo Banks	Established Banks
Capital (LEV)	-127.7*** (-22.97)	-117.9*** (-4.54)	-126.8*** (-22.15)
Asset	22.89*** (9.40)	9.986 (1.30)	24.66*** (9.54)
Management	0.104** (1.98)	0.361 (1.49)	0.105* (1.85)
Earnings	-13.27*** (-3.51)	-34.16** (-2.05)	-13.58*** (-3.44)
Liquidity	0.682*** (4.14)	0.325 (0.35)	0.658*** (4.07)
Sensitivity	1.210* (1.80)	-0.658 (-0.26)	2.005*** (2.76)
GDP	-12.41*** (-5.53)	-9.260 (-0.88)	-11.35*** (-4.84)
Total Observations	710223	31419	678804
# of Bank Failures	446	49	507
Log Likelihood	-792.8	-49.0	-734.8
AIC	1603.7	115.9	1487.7
BIC	1706.9	191.1	1590.5

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Regulatory Types – Logit Estimation

	FDIC	FRB	OCC	OTS	FDIC	FRB	OCC	OTS
Capital (LEV)	-146.7*** (-15.11)	-237.1*** (-6.12)	-103.2*** (-11.49)	-99.24*** (-8.17)				
Capital (RBC)					-177.3*** (-16.31)	-205.2*** (-6.53)	-128.6*** (-11.86)	-107.1*** (-8.30)
Assets	26.08*** (6.39)	21.42* (1.69)	19.04*** (4.11)	27.17*** (4.64)	31.14*** (8.17)	34.61*** (4.10)	23.36*** (4.49)	28.18*** (5.49)
Management	0.0217 (0.11)	0.0673 (0.08)	0.612** (2.37)	0.329** (2.34)	-0.0664* (-1.66)	-0.577 (-1.39)	0.700** (2.50)	0.348* (1.76)
Earnings	-12.12** (-2.01)	-9.724 (-0.52)	-17.30** (-2.43)	-10.25 (-1.09)	-7.963 (-1.30)	-22.23 (-1.43)	-16.62** (-2.08)	-19.55** (-2.02)
Liquidity	0.550 (1.26)	-3.951* (-1.90)	0.467** (2.48)	1.653*** (2.73)	1.062** (2.03)	-2.347 (-1.35)	0.689 (1.47)	1.643*** (2.79)
Sensitivity	2.464* (1.72)	6.099* (1.70)	2.829** (2.35)	-3.358* (-1.65)	1.799 (1.21)	-0.0315 (-0.01)	2.166 (1.33)	-3.434* (-1.74)
GDP	-9.987*** (-2.84)	-6.449 (-0.62)	-17.71*** (-4.34)	-9.987*** (-2.84)	-10.94*** (-3.00)	-9.124 (-0.97)	-17.75*** (-3.84)	-17.50*** (-3.25)
Constant	-2.530*** (-3.46)	4.627** (2.05)	-3.582*** (-5.92)	-4.146*** (-4.69)	0.751 (0.95)	5.991** (2.36)	-1.153 (-1.45)	-2.654*** (-2.68)
Total Obs.	405839	68413	160996	74969	405839	68413	160996	74969
# of Banks	9724	2036	4903	2219	9724	2036	4903	2219
Log Likelihood	-324.0	-43.3	-230.9	-160.8	-310.4	-60.1	-211.2	-170.0
AIC	666.1	104.6	479.7	339.7	638.8	138.2	440.4	358.0
BIC	764.3	186.8	569.6	422.7	737.0	220.4	530.3	441.1

Standardized beta coefficients; t statistics in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 15: Regulatory Types – Forecasting Ability

Leverage Model	**Distress** correctly detected	falsely detected	**Risk-Based Capital Model**	**Distress** correctly detected	falsely detected
FDIC	85.71%	-	FDIC	86.98%	-
FRB	89.29%	-	FRB	82.14%	-
OCC	71.55%	-	OCC	74.14%	-
OTS	62.12%	-	OTS	59.09%	-