Achieving a Balance between the Avoidance of Banking Problems and their Resolution
Can Financial Cycle Dynamics Predict Bank Distress?

Giannoula Karamichailidou[1], David G. Mayes[1], and Hanno Stremmel[2]

Abstract

The global financial crisis has emphasised the importance of the financial cycle in contributing to bank failures. In this paper we consider how far it is possible to anticipate problems in banks by using early warning indicators available from published information on the financial cycle in the economy. We use a traditional z-score model that incorporates bank-specific, banking structure and macroeconomic variables to which we add financial cycle indicators. We test these models on an unbalanced panel of 2239 European banks over the period 1999-2014. We find that the financial cycle adds noticeably to the ability to predict bank distress up to two years into the future.

Introduction

Financial crises and their associated bank failures have been a common but unwelcome feature of economic life since the financial sector has had any importance. Furthermore, as Reinhart and Rogoff (2008) illustrate in their analysis of 800 years of such crises, while each crisis has its own characteristics and causes, many of the features of such crises are disappointingly similar. The regularity in the features of crises should mean that to some extent they are predictable both at the aggregate and the individual bank level. Optimists therefore argue that by focusing on such regularities one could reduce the chance of crises and be able to act early on those that do emerge. In many respects that is the main justification for macro-prudential analysis and, in the European context, is the role of the European Systemic Risk Board. Our focus, however, is at the individual bank level. While individual banks can fail at any time for idiosyncratic reasons, bank failures tend to be associated with problems in the banking system and economy as a whole. The problem is to sort out which of the banks are most at risk, as while many stabilising measures apply to the whole sector or economy, some need to be applied to individual institutions. Hence exposing macroeconomic pressures is only part of the concern and even if they cannot be forecast reliably there is still usefulness in exposing risks for individual banks.

If intervention in banks can be triggered early, then it is likely that the losses will be reduced and the chance of a bank recovering before failure and hence avoiding the costs of resolution will be higher. Expanding the use of contingent convertible securities (CoCos) and other debt that can be bailed in on the strength of objective market indicators is an aspect of trying to achieve this. Yet in practice anticipating problems has been difficult to do. As Garcia (2012) pointed out in the case of the US in the global financial crisis (GFC), ex post material loss reviews indicated that the signals of problems in banks that failed were evident with the benefit of hindsight but not acted on in practice – hence the interest in automatic triggers. In part, as Reinhart and Rogoff (2008) emphasise in the title of their book *This Time Is Different*, it is because the signals are explained away. But it is also the case that the signals are somewhat different on each occasion, as with the GFC.

A striking feature of the GFC was that it illustrated a major swing in the financial cycle, indeed to some extent this is simply the description of a crisis. Some crisis explanations, such as that by Minsky (1986) focus entirely on this dimension. One might therefore expect the cycle to lie at the heart of predictive models. On the whole, however, prior early warning models have incorporated macro-economic, bank structure and bank specific indicators (see Männasoo and Mayes (2009) and Mayes and Stremmel (2014) for surveys) and have placed less weight on variables relating to the financial cycle. In this paper, therefore, we seek to expand that analysis by adding financial cycle indicators to the traditional model. While there is a strong possibility that we will merely improve our ability to predict the last crisis, the variables we include have featured strongly in other crises as well (Demirgüç-Kunt and Detragiache, 1998, 1999; Hardy and Pazarbasioglu, 1998; Hutchison and McDill, 1999). Most importantly, we find that financial indicators can predict one two and even three years ahead. Of course such prediction is not particularly accurate and some failures will be missed and some banks will be mistakenly described as being at risk. However, even a limited ability is of value. Moreover, the data we use, which are all publicly available, through BankScope, the Bank for International Settlements (BIS) and the International Monetary Fund (IMF), are inferior to the information that banks have available to themselves and to that provided in confidence to their supervisory authorities. Hence the actual ability to act early should be greater than that indicated by our models.

Financial sector supervisors use balance sheet and income statement financial ratios to monitor and assess the risks of individual banks (e.g., Poghosyan and Cihak, 2009). However, the 2007/08 Global Financial Crisis came as a surprise in most economies. An adequate early-warning system could have enabled policy makers to identify vulnerabilities in the financial system in advance and deal with potential threats accordingly (Mayes and Stremmel, 2014). However, such early-warning system was not in place in most countries. Our concern here is to construct an early warning tool relating to measures and indicators of financial stress, which takes more factors into account, most especially the types of variables that are being addressed by the European Systemic Risk Board (ESRB) and other macro-prudential regulators (see for example, ESRB, 2014). This adds measures relating to the financial cycle, economic cycle, bank structure and individual bank characteristics.

The present paper is exploratory, using data from EU-15 countries, but we are planning to expand our sample to as many of the European countries as the data will allow us.

In the rest of this paper, we begin in Section 1 by developing the context for our models in existing research. Section 2 sets out the model, Section 3 explains the data, while Section 4 analyses the main results and provides a range of robustness tests. Section 5 concludes.

1 Context

The high costs of the present global financial crisis have refocused attention on both reducing the chance of future crises and reducing the costs of any such crises that do occur.[1] Action has taken place on a number of fronts, with increases in capital buffers and liquidity provisions under Basel 3 and the implementation of a wide range of tools for enabling the resolution of large banks without their having either to cease operating or draw on taxpayer funds, using the 'bailing in' of creditors in particular as a form of 'loss absorbing capacity'. Furthermore, the problem of banks being international but the authorities that control them being limited by the boundaries of national jurisdiction are being addressed through the Financial Stability Board (FSB) and in the euro area through Single Supervisory Mechanism (SSM) and the Single Resolution Mechanism (SRM) and their associated institutions. By having recovery and resolution plans in place it is hoped that the authorities and the banks themselves will be able to act more rapidly and with greater skill. The structure of banking groups themselves is being limited with the implementation of the 'Volcker rule' in the US

[1] While the GFC may have been particularly horrific, all banking crises are associated with significant reduction in GDP and consequently welfare loss (see for example, Hoelscher and Quintyn, 2003, Dell'Ariccia et al.,2008, Cecchetti et al., 2009, and Jordà et al, 2010).

and similar measures in the UK, France, Germany and other countries[2] although not at the EU level yet despite the Liikanen Report.

The temptation at this stage of the reaction to the GFC is to do everything: to reduce risk taking; to increase the ability to absorb shocks; to start corrective measures early; to improve the tools for resolving problems and to create a better functioning international crisis management framework. However, all these measures come at a cost, whether it relates to making banking services more expensive, less available or even simply to lowering the possible rate of economic growth. Cost/benefit analyses attached to legislative proposals (eg European Commission, 2012; RBNZ, 2012) suggest that the benefits greatly outweigh the costs. It is therefore difficult to know where to stop and to judge which of these measures should be pursued furthest so that we end up with a balanced system.

It is not even possible to treat each aspect individually as some affect others. Ensuring a clear and workable approach to resolution which removes the bank from the control of the shareholders and the management will have a strong impact on how the bank is run, as those groups will wish to avoid that outcome. Indeed in its calculation of the benefits from its bail in scheme (labelled Open Bank Resolution) the Reserve Bank of New Zealand (2012) argues that the main gain is going to come from encouraging earlier and cheaper means of voluntary resolution and that bail ins will be rather unlikely in practice.

In this paper we touch on just one aspect of the changes, namely, the ability to detect problems earlier and act upon them before the problems and their associated losses mount. Ideally, if problems can be foreseen, an intervention can be sufficient that they are contained and do not turn into a full blown crisis. We look simply at being able to predict problems in individual banks but the recent financial crisis exposed not just the interconnectedness of financial institutions but the inadvisability of believing that if one could supervise each individual financial institution well this would ipso facto result in having a stable financial system as a whole. Although this is addressed by the development of macro-prudential policies, those also have several facets. While many relate to problems across the whole sector and then consider individual institutions from a top down perspective, ideally our analysis of problems in individual banks would be weighted by their contribution to systemic

[2] See Loi 2013-672 du 26 juillet 2013 de séparation et de régulation des activités bancaires, J.O. n°173 du 27 juillet 2013, p. 12530 and Gesetz zur Abschirmung von Risiken und zur Planung der Sanierung und Abwicklung von Kreditinstituten und Finanzgruppen v. 7.8.2013, BGBl. 2013 I p. 3090 for the French and German implementations.

risk in the financial system as a whole. In that way one would not merely identify the problem banks but the importance of these problems, perhaps in an analogous way to how Engle et al. (2014) consider the systemic implications of capital levels in specific European banks. However, the authorities are well aware of the relative importance of their banks to the stability of the overall system. Unlike many of the other measures what we are discussing is of very low cost.

2 The Model

Our basic approach is straight-forward. Banking problems are a function of bank-specific, bank structure/market, macroeconomic and financial cycle variables. In this section we explain our choice of those variables, including our measures of banking problems, and the models we use to estimate the relationships. Our choice is deliberately conventional, not least to make our analysis as comparable as possible with the existing literature.

Most previous research has tended to use some form of logit or probit model to explain banking failures or distress, because they take the occurrence of such failure or distress as their dependent variable. Hence, they are seeking to explain a binary variable that holds the value 1 in the case of a crisis, failure or distress and 0 otherwise, and the logit and probit transformations enable this to be handled in a metric which permits normal regression analysis (Laeven and Valencia, 2013). One difficulty in applying this method in our case is simply that there have not been all that many clear bank failures in Europe unlike for example in the US. Hence we would have a very thin data set for explaining failure. However, we are not seeking simply to explain failure but to identify when banks are getting into difficulty so that early action could take place. Hence the normal indicators of potential difficulty are appropriate, the two most widely used being z-scores and distance to default.

z-scores

In this paper we focus on z-scores, because this permits us to use a larger sample, and leave distance to default for a subsequent study. z-scores are accounting-based measures, obtained from balance sheet and income statements of the banks and financial institutions under investigation (see for example, Thomson, 1992; and Cole and Gunther, 1998), which focus mainly on credit risk. However, distance to default is a market-based measure, which can improve the forecasting ability of a model that uses just accounting-based measures. The advantage of market-based indicators over accounting-based indicators is that they are forward-looking (see for example, Chan-Lau and Sy, 2007). Nevertheless, the market-based measures can be applied only to listed banks. There are many unlisted banks in the EU, consequently, a combination of both accounting-based and market-based indicators in the analysis would provide a more complete picture of the European banking system.

z-scores show the number of standard deviations that a bank's rate of return on assets can fall in a single period before it becomes insolvent. A higher z-score signals a lower probability of bank insolvency (Bertay et al., 2013). They are extensively used in the literature. Boyd et al. (1993) examine whether mergers of bank holding companies (BHCs) with nonbank financial firms in the US affect the risk of the BHCs and uses the z-score to estimate the probability of bankruptcy where bankruptcy is defined as the point when equity is insufficient to cover losses. Boyd et al. (2006) examine the relationship between bank concentration and bank stability proxied by the z-score. Schaeck and Cihak (2010) and Beck et al. (2013) examine the relationship between bank competition and bank stability employing the z-score as a proxy for bank stability or soundness. Furthermore, Bertay et al. (2013) use z-scores to compare the probability of bank insolvency of large banks conditioning on their performance and business models while Saunders et al. (2014) examine the relationship between non-interest income and bank performance in the outset of banking structural reforms proposed after the Global Financial Crisis (GFC) breakout focusing on the US market. The authors use the z-score to measure bank risk-taking.

The accounting z-score can be calculated as follows:

$$z_{i,t} = \frac{ROA_{i,t} + (\frac{E}{A})_{i,t}}{\sigma(ROA)_{i,t}}\ , \qquad (1)$$

where $ROA_{i,t}$ is the return on assets of bank i at in year t, E/A is the equity to asset ratio, and $\sigma(ROA)$ is the standard deviation of return on assets calculated over the whole sample period as in Köhler (2012).[3] The z-score indicates the number of standard deviations that a bank's rate of return on assets can fall in a single period before it becomes insolvent. A higher z-score signals a lower probability of bank insolvency (Bertay et al., 2013). Even with a z-score we cannot get away from problems with the distribution of the dependent variable. It is effectively bounded in a downward direction and almost certainly skewed. In line with

[3] In common with the literature we also explore a three-year window but this tends to be unstable.

Demirguc-Kunt and Huizinga (2010), Houston et al. (2010) and Laeven and Levine (2009), we take the natural logarithm of the z-score to ameliorate the problem with its skewed distribution.

Independent variables

We build on the considerable literature published on early warning indicators to identify the variables that help identify and predict vulnerabilities in the financial system.[4] Explanatory variables fall into four main categories:

- Bank specific variables drawn from accounting or stock market data
- Bank structure and financial market variables
- Macroeconomic variables
- Financial cycle variables.

However, there are relatively few studies that look at banking distress in Europe for us to build on. Poghosyan and Čihák (2009) examine the causes of bank distress in Europe (EU-25) from 1990s to 2008 and identify indicators that assist in distinguishing sound from vulnerable banks. They use several versions of the logistic probability model while their explanatory variables are lagged by one period. The authors define bank distress through the lens of media reports when negative items start to be reported about a particular bank. They find that capitalization, asset quality and profitability have a good predictive power while cost-to-income ratios and basic liquidity indicators do not seem to predict bank distress. We build on this by adding a wider range of variables and trying to forecast further ahead.

Like Poghosyan and Čihák (2009) most of the previous studies use logit models, with a few examples of z-scores. There is however no obvious reason why the choice of the metric for the dependent variable should have much implication for its determinants. In their distance to default model Blundell-Wignall and Roulet (2013) use variables relating to macro-prudential, risk-taking, leverage, business model and diversification. They find that for smaller nationally-focused banks, bank's beta, the leverage ratio, and the house prices are significant determinants of the DTD. For global-statistically significant banks, apart from the above

[4] Yucel (2011) provides an extensive literature review on early warning models from 1971 to 2011. The most commonly used model is a logit regression, where probabilities of a financial crisis are related to various explanatory variables.

mentioned determinants, derivatives exposure, trading assets, wholesale funding, and relative size also significantly explain DTD variation.

Bank-specific variables

We have followed the commonly used explanatory variables in the literature in choosing which variables to use in our analysis. This adds new references to a much wider meta-study of previous work set out in Mayes and Stremmel (2014) which we do not reproduce here. In general terms these variables run across the six categories thought relevant by the FDIC in its own monitoring of banks in the US (see FDIC 2015), which goes by the acronym of CAMELS where the components are C, capital adequacy, A, asset quality, M, management competence and expertise, E, earning ability and strength, L, liquidity, S, sensitivity to market risk. However, most authors find it difficult to obtain measures for M and S. We have also managed to find data on some other related measures that we have added, as shown in the last column of the Table. Our choice is constrained by data availability. Several authors consider various of the CAMELS variables. Köhler (2012), for example, examines the impact of loan growth and business model on bank risk, estimated by the z-score, in 15 EU countries, finding that banks with high rates of loan growth are riskier but those that increase their non-interest income become more stable. Schaeck and Cihák (2010) examine the relationship between competition and bank soundness, focusing on European banks and single-market banks operating in rural areas in the U.S. They find that smaller banks' soundness measures respond more strongly to competition and that weak banks, in terms of their soundness, benefit less from competition than do sound institutions.

Bank structure and financial market variables

Work on issues of banking structure has been more limited. Perhaps the most relevant is Uhde and Heimeshoff (2009) who investigate whether the national banking market concentration has a negative impact on European banks' financial soundness as measured by the z-score while controlling for macroeconomic, bank-specific, regulatory, and institutional factors. Their sample is comprised of banks from the EU-25 countries, covering the years 1997-2005. They find a negative relationship between market concentration and European banks' financial soundness. This is echoed by Männasoo and Mayes (2009) in the context of the central and eastern European countries (13 of which are now part of the EU) using a

Herfindahl Index to account for concentration and consider the share of the market accounted for by state owned banks, although the latter is not relevant in the present context. The same approach is followed by Gramich and Oet (2011) who argue that structural fragility such as concentration and dependency of a financial system need to be taken into account when designing early warning systems to predict distress. We therefore follow this lead and use the concentration index.[5]

Macroeconomic variables

There is extensive evidence that adverse macroeconomic conditions can lead to banking problems (Borio and Drehmann, 2009). Flannery (1998), Curry et al. (2007), Bharath and Shumway (2008) show that macroeconomic and market-based indicators contain useful information in predicting bank distress. Many of the obvious variables have been included. Männasoo and Mayes (2009) for example consider not just GDP and inflation as proxies to control for business cycle effects as do Demirgüc-Kunt and Detragiache (2005) but also include more financial variables such as interest rates, the change in the exchange rate and the ratio of private lending to GDP. Here we classify these latter variables as indicators of the financial cycle which we turn to in the next subsection. As Stremmel (2015) shows, the periodicity of macroeconomic and financial cycles is clearly different in Europe over the last 30-40 years.

Financial cycle variables.

While the bank specific variables identify which banks are weakest at any one time it is the cyclical variables which give the best leading indicators of when those weakest banks will be pushed into distress and even ultimately failure. While the macroeconomic cycle worked well in the case of the central and eastern European countries before the global financial crisis (Männasoo and Mayes, 2009), it is the financial cycle variables that have shown most fluctuation since then and hence prima facie may be the better leading indicators of problems when economic and financial cycles coincide. Both sets of variables are however needed as macroeconomic cycles have a higher frequency than financial cycles and may hence indicate incipient problems when the financial indicators do not. Babecký et al. (2012), in their examination the stylized facts of banking, debt and currency crises, find that growth of

[5] We are grateful to Leone Leonidas for suggesting that the square of concentration should also be added as in his work he found that relationship was curvilinear and indeed the effect varied from negative to positive depending on the level of concentration.

domestic private credit, increasing FDI inflows, rising money market rates as well as increasing world GDP and inflation were common leading indicators of banking crises. This leads them to recommend the use of a composite early warning index rather than seeking the best single indicator.

There are two obvious groups of financial variables to include. The first relates to money and credit aggregates. If all banks are expanding lending particularly rapidly at any one time then the chances are that risks are being built up as such rapid growth tends to be reflected in declining credit quality. Köhler (2012), for example, finds that banks become more risky when aggregate credit growth is excessive. The second relates to asset prices, particularly real estate. Barrell et al. (2010), for example, use property prices in their analysis to predict systemic banking crises.

While some authors focus on just one group of variables and other such as Drehmann and Julius (2014), who find that credit-to-GDP and debt service ratio also perform well as early warning indicators, use both, it is there interation which has proven particularly damaging in recent years. Using a sample of 14 countries over the previous 170 years, Jorda et al. (2015) argue that it is asset price bubbles leveraged by credit booms that create the worst damage. They also find that it is real estate price booms that cause the more damage. Stock market collapses can sometimes be absorbed with limited effect, as in 1987 and 2001, although it is arguable that the swift response by the monetary authorities, particularly in the US, has laid the ground for greater subsequent instability.

Recent evidence has shown that (i) financial cycle peaks tend to be associated with systemic banking distress and (ii) financial cycles are helpful in the timely detection of distress in the financial system (see for example Borio, 2014 and Stremmel, 2015). Further, Aizenman et al. (2013) show that real sectors can be severely affected by movements of the financial cycle.

Thus, our main research question is whether financial cycles provide additional information about impending banking distress. Since we are also including individual financial variable for the economy our concern with the financial cycle is whether bank failure varies over the phases of the cycle. We distinguish two states in the cycle: when it is moving down and when it is moving up.

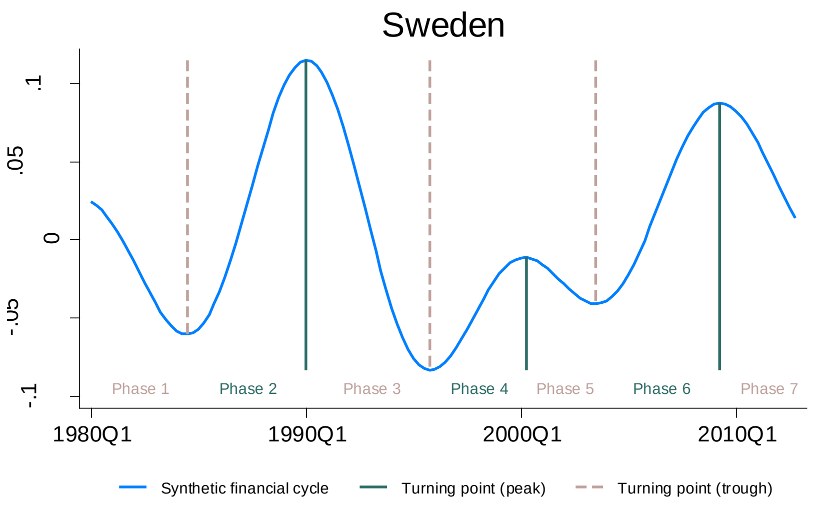
Financial Cycle Metric

Vulnerabilities within a financial system reflect not just adverse shocks but cyclical movements of financial influences which may pose risks to financial stability and may lead to serious financial and macroeconomic tensions. One of the key issues is that the finance sector is prone to overshooting. Furthermore, asset prices reflect anticipated returns over the future life of the asset. Since the actual returns are unknown beforehand such prices can vary widely for longer term assets on the basis of quite limited news. Markets also seem to be subject to 'herding', which means that, rather than a limited number of people changing their minds on a particular occasion, many people make a similar change rapidly.

Financial cycles are thus different from business cycles, both in their length and amplitude. The typical business cycle is around four or five years in length whereas the financial cycle is usually two to three times as long. It also tends to have greater asymmetry, with sharper falls and longer recovery periods. While the relevant variables that contribute to financial cycles are well-known there is no accepted measure of the cycle as such. Stremmel (2015) therefore approximates the cyclical regularities using filtering techniques, since no "natural" financial cycle measure is available – in contrast to the real economy (business cycle). This financial cycle thus condenses the financial information which is relevant for overall financial conditions and development within a country into one single indicator. Various different combinations of asset prices, credit aggregates and banking sector variables are explored but Stremmel (2015) concludes, on the basis of European data, that the best fitting financial cycle measure includes credit-to-GDP ratio, credit growth and house prices. It is therefore this indicator which we incorporate although we do test its robustness.

Figure 1 illustrates how the financial cycle measure operates, using the example of Sweden. The financial cycle is divided into two phases, each phase lasting from one turning point to the next. They hence represent either expansion or contraction. The hypothesis advanced to underpin this is that markets and financial institutions are subject to different pressures and behaviour in the two phases. Although Minksy (1986) may have a rather more complex set of phases in the financial cycles he describes, here the concern is that in the contraction phase, banks are faced with a need to recapitalise, at least some of which will be achieved through trying to contract lending. Asset prices will also fall smartly as banks try to increase their liquidity. There is thus a distinct change in behaviour represented by the direction of change of the cycle and not just by the levels of the variables from which it is calculated.

Figure 1 Financial Cycle



Based on: Stremmel (2015)

Data and Sample

Our sample comprises annual data on 2,239 banks in the EU-15 countries over the period 1999-2014 (see Tables A.1 and A.2 in Appendix A for more details).[6] While the end date is the most recent available, the starting date is also constrained by the availability in the database. The accounting data on the banks in our sample are obtained from Bankscope. Data on our macro-economic variables are obtained from International Financial Statistics (IFS) of IMF, while our banking sector and macro-financial data are obtained from Bank for International Settlements.

The variables are described with their mnemonics in Table 1. As expected there is inevitably some overlap among the bank specific variables (Table 2) but the extent does not appear sufficiently large to offer much fear of providing poorly determined coefficients due to multicollinearity. Not surprisingly GDP growth and inflation are correlated but the correlation coefficient, while significant at 1%, is only 0.21, so again their joint inclusion in the explanatory equations should pose little problem. Somewhat more surprising is the lack of correlation among the financial cycle variables.

[6] i.e it is the EU as it stood in 1999 at the start of our sample, so Austria, Finland and Sweden are included but Cyprus, Malta and central and eastern European countries which have joined since then are not – an omission that will be rectified in subsequent analysis.

The form of our model was laid out earlier, with z-scores being explained by bank specific, macroeconomic, banking system structural and financial cycle variables set out in Table 1. We also include a dummy variable for the phase of the $Financial\_cycle$ that takes the value of 1 when the cycle is on the downside and 0 otherwise. We also include bank and time fixed effects, so that each bank can differ in its basic z-score from the average and so that each year can reflect a different setting of z-scores.

Table 1 Descriptive statistics of the variables used

Variable Name	Variable Description	Mean	Median	Std Dev	Minimum	Maximum
Z-score	The sum of the mean return on assets and the mean ratio of equity to assets divided by the standard deviation of the return on assets	35.92	22.81	45.15	1.18	300.98
CI	Cost to income	64.23	63.48	24.98	7.24	182.50
ECSTF	Equity to customer & short term funding	18.33	9.50	39.26	1.06	319.77
LAA	Liquid assets to total assets	24.34	16.29	22.83	0.32	97.16
LLPA	Loan loss provisions to total assets	0.42	0.23	0.69	-0.54	4.27
NIIGR	Non-interest income to gross revenues	34.32	30.82	29.01	-66.90	114.42
NIM	Net interest margin	2.10	1.93	1.47	-0.62	8.21
TA	Total assets (in millions)	28010	2251	102481	26	767213
BC	Bank concentration	65.81	66.35	16.85	27.01	96.15
BSZ	Banking sector z-score	15.39	14.85	6.96	2.19	39.39
GDP_growth	Annual GDP growth in percentages	1.46	1.77	2.55	-5.64	8.42
Inflation	Annual change in CPI	2.07	2.07	0.96	-0.29	4.48
DSRNFC	Debt service ratio of non-financial corporations	35.70	33.95	12.63	15.97	79.77
DSRHHS	Debt service ratio of households	15.78	12.98	6.95	7.89	33.01
MC_GDP	Market capitalization to GDP	72.60	65.59	42.40	13.48	210.51
M3_GDP	Nominal M3 to GDP	129.28	90.16	160.17	42.78	831.33

So in effect we use a fixed-effects panel data model with robust errors. Our panel is unbalanced so that we can include each bank for as many years as possible rather than restricting ourselves just to those banks that survive for the entire period. While there might be some reason for excluding new banks, as they sometimes behave differently (Mayes and Stremmel, 2014), it makes little sense to exclude banks that have merged or been divided during the period. In particular we do not want to exclude banks that have failed as they will have contributed the most useful downside values that policymakers will want to identify in the future. This leaves us with 19,005 observations in total. The explanatory variables that are not expressed in percentages or ratios undergo logarithmic transformation to reduce any skewness and heteroskedasticity problems that might occur in the regression analysis, as in Benston and Hagerman (1974). Specifically, these variables are total assets (TA), net interest margin (NIM) and the banking sector z-score (BSZ).

For our model to be useful it needs to forecast, so in our base model, all the explanatory variables are lagged by one period, by one year in our case. This will also mitigate reverse causality concerns as in Saunders et al. (2014), because to some extent some of the bank specific variables are effectively components of the contemporaneous z-score. There are, however, some complications as we have no reason to believe that all variables have the same forecasting ability. It may very well be that some of the cyclical variables can forecast rather better further ahead, as at shorter lags they may already be changing as the downturn starts to emerge (see for example, Uhde and Heimeshoff, 2009; Drehmann and Julius, 2014). Thus, we also explore specifications where we lag our macro-economic, banking sector and macro-financial variables by two periods. Lagging the bank specific variables further does not produce well determined estimates. Indeed we would expect this because if adverse indicators occur both the banks themselves and the authorities will tend to react thus weakening the relationship. In any case if there were a clear longer lag relationship there would be much less of an early warning problem than we observe and banks and authorities would not get caught out so easily in failing to identify incipient problems.

We could try altering the structure of the model to formulate it with an underlying determinant and an error correction mechanism but while this would certainly fit the data much better as z-scores are very persistent, this would re-open the problems of simultaneity.

Table 2 Correlation matrix of independent accounting-based variables

	CI	ECSTF	LAA	LLPA	NIIGR	NIM	TA	BC	BSZ	GDP_growth	Inflation	DSRNFC	DSRHHS	MC_GDP	M3_GDP
CI	1.00														
ECSTF	-0.06***	1.00													
LAA	0.054***	0.02***	1.00												
LLPA	0.004	0.03***	-0.18***	1.00											
NIIGR	0.17***	0.11***	0.27***	-0.03***	1.00										
NIM	-0.05***	0.07***	-0.26***	0.34***	-0.23***	1.00									
TA	-0.11***	-0.15***	-0.06***	-0.06***	0.01	-0.36***	1.00								
BC	0.005	0.02**	-0.29***	0.07***	-0.16***	0.17***	-0.06***	1.00							
BSZ	-0.003	-0.06***	0.04***	-0.07***	0.05***	0.03**	-0.19***	-0.15***	1.00						
GDP_growth	-0.07***	-0.012	0.12***	-0.23***	0.05***	-0.04***	-0.07***	-0.08***	0.13***	1.00					
Inflation	0.010	0.014*	0.04***	0.03***	-0.003	-0.01	-0.01	-0.01	-0.21***	0.21***	1.00				
DSRNFC	-0.03***	0.06***	0.01***	0.07***	-0.05***	0.01	-0.07***	0.15***	-0.19***	-0.14***	0.23***	1.00			
DSRHHS	-0.03***	0.05***	0.05***	0.09***	0.02*	-0.05***	0.01	-0.10***	-0.38***	-0.07***	0.24***	0.27***	1.00		
MC_GDP	-0.09***	0.02**	0.22***	-0.17***	0.15***	-0.13***	-0.02**	-0.36***	0.06***	0.35***	-0.04***	0.10***	0.48***	1.00	
M3_GDP	-0.08***	-0.04***	0.34***	-0.10***	0.16***	-0.23***	-0.002	-0.54***	0.18***	0.19***	0.11***	0.43***	0.57***	0.51***	1.00

3 Multivariate analysis

The main results are shown in Table 3, where column (1) shows the full model. It is immediately clear that most of the variation is left unexplained but then this is not surprising with panel data and where forecasting has been poor traditionally. The question at issue is whether the information that is included is robust enough to detect future problems.

Five of the seven bank specific variables seem to be able to explain the future z-score, along with total assets, which acts as a scale variable. The signs are largely as expected. If costs are high relative to income then the bank is relatively inefficient. Similarly the greater equity is compared with short-term funding then the greater the ability of the bank to withstand funding shocks. However, this does not seem to work well when we consider liquid assets where the coefficient is negative. More liquid assets normally have a lower rate of return but that is nt a sufficient explanation. Greater loan loss provisions are a clear sign of weakness, since these provisions are normally only made when the bank realises that it loan portfolio is impaired. Clearly if banks if the expected loan losses were similar across banks then have greater provisions would indicate a safer bank. Net interest margin is also positive, indicating a more profitable and hence stronger bank.

To get a flavour of what the remaining variables that are economy wide offer to the overall explanation we show in the remaining columns of Table 3 what happens if they are omitted. Thus column (6) leaves them all out and we can see that they contribute somewhat more than 5% to the total explanation of the z-scores but around a third of the total explanation.

This is relatively small but at least most of the effects are statistically significant and have expected signs. Taking the bank structure variables first, concentration shows a clear nonlinear relationship, with the overall relationship turning positive as concentration increases. A higher z-score for banking as a whole, however, seems to presage difficulty for individual banks.

Turning to the macroeconomic variables (column (4)), they have the expected signs. As GDP growth rises so z-scores two years ahead will tend to fall. Since the typical length of the business cycle is about four years, what we see here is that a boom presages a fall. Inflation on the other hand is positively related to the z-score two years ahead. One possible explanation of this is that with rising prices collateral values may rise relative to debt.

Table 3 Contribution of independent variables to the model

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	10.318***	9.697***	9.669***	8.920***	8.561***	7.915***
	(14.05)	(15.27)	(15.22)	(15.08)	(14.56)	(13.38)
CI	-0.0016***	-0.0016***	-0.0016***	-0.0015***	-0.0014***	-0.0014***
(Cost to income)	(-3.88)	(-3.83)	(-3.86)	(-3.44)	(-3.26)	(-3.19)
ECSTF (Equity to customer & short	0.0015***	0.0017***	0.0017***	0.0020***	0.0020***	0.0020***
term funding)	(3.58)	(4.26)	(4.32)	(4.75)	(4.79)	(4.76)
LAA	-0.0012	-0.0013	-0.0013	-0.0016**	-0.0019**	-0.0018**
(Liquid assets to total assets)	(-1.39)	(-1.65)	(-1.62)	(-2.06)	(-2.55)	(-2.46)
LLPA	-0.0477***	-0.0593***	-0.0620***	-0.067***	-0.0558***	-0.0569***
(Loan loss provisions to total assets)	(-4.56)	(-5.64)	(-5.90)	(-6.18)	(-5.35)	(-5.49)
NIIGR	-0.0004	-0.0003	-0.0003	-0.0003	-.00003	-0.0002
(Non-interest income to gross revenues)	(-0.80)	(-0.65)	(-0.61)	(-0.58)	(-0.51)	(-0.45)
NIM	0.0502***	0.0412***	0.0421***	0.0307***	0.0232**	0.0289**
(Net interest margin)	(3.65)	(3.20)	(3.27)	(2.66)	(2.05)	(2.51)
TA	-0.3145***	-0.2676***	-0.2675***	-0.2246***	-.02128***	-0.2177***
(Total assets)	(-9.26)	(-8.91)	(-8.89)	(-8.49)	(-8.07)	(-8.22)
BC	-0.0118***	-0.0218***	-0.0212***	-0.0245***	-0.0224***	
(Bank concentration)	(-3.24)	(-6.26)	(-6.21)	(-7.08)	(-6.40)	
BC^2	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***	
(Bank concentration squared)	(3.03)	(5.56)	(5.45)	(6.26)	(5.80)	
BSZ	-0.0392*	-0.0562***	-0.0491***	-0.0525***	-0.0399**	
(Banking sector z-score)	(-1.80)	(-3.28)	(-2.91)	(-3.02)	(-2.36)	
GDP_growth	0.0062	0.0039**	0.0045**	-0.0142***		
(Annual GDP growth)	(1.39)	(2.22)	(2.55)	(-8.74)		
Inflation	-0.0354***	-0.0134**	-0.0137**	0.0080		
(Annual change in CPI)	(-2.74)	(-1.99)	(-2.06)	(1.32)		
DSRNFC (Debt service ratio of non-	0.0001	-0.0019	-0.0015			
financial corporations)	(0.07)	(-1.22)	(-0.96)			
DSRHHS	-0.0231***	-0.0179***	-0.0192***			
(Debt service ratio of households)	(-5.14)	(-4.42)	(-4.81)			
MC_GDP	0.0003	-0.0013***	-0.0012***			
(Market capitalization to GDP)	(0.81)	(-6.08)	(-5.55)			
M3_GDP	0.0029***	0.0060***	0.0060***			
(Nominal M3 to GDP)	(3.48)	(10.06)	(9.98)			
Financial cycle dummy	-0.0192**	-0.0223***				
	(-2.20)	(-2.59)				
Number of observations	9,385	9,385	9,385	9,385	9,385	9,385
R^2 (within)	0.1912	0.1573	0.1564	0.1227	0.1109	0.1029

Notes: In all specifications the bank-specific variables and debt to service ratio are lagged by one period while the remaining variables are lagged by 2 periods. Specification (2) differs from Specification (1) in that the time effects are removed. These are clearly an important contribution to the overall explanation.

However, it is not worth pursuing these factors far as the macroeconomic cycle is clearly offset by the financial cycle. In the full model both variables change sign and become insignificant. To quite an extent this is because of the time effects. However, time effects are not helpful to a forecasting model as they are of unknown size at the time of forecasting.

The financial cycle variables give an idea of impending problems. Risks are built up in the up phase of the cycle and realised in the down phase which is when banks get into difficulty. Hence both market capitalisation as a ratio of GDP and the debt service ratio have negative signs. As credit and debt rise, so the potential for an adverse reaction when economic times get harder increases. Financial crises normally coincide with economic downturns but not all economic downturns lead to a financial crisis. It is noticeable that there is some variation in the significance of these terms across the various specifications. In part this is because we only have one full financial cycle for many of the countries and hence there is some relation between this and the time dummies. However we can also see from Table 4 that this is partly because of the differences in lag structure.M3 on the other hand shows a positive relationship, which is more difficult to interpret. this may simply be because of the role of deposits, which act as a stabilising influence.

Column (2) of Table 3 shows the results of adding the financial cycle dummy. As noted above the financial cycle variable is composed of weights on the main factors we consider: credit, money and asset prices. Our suggestion is that z-scores are affected by the phase of the cycle as well as by the absolute value of the contributing variables. We see that this indeed the case and that in the down phase z-scores are lower – given the values of all the other variables in the model.

On might interpret this as the cycle picking up misspecification elsewhere in the model. We consider below whether all of the coefficients in the model vary across the phases of the cycle rather than just the simple step change between the two phases that we have explored here.

The final difference shown in Table 3, between columns (1) and (2) is the inclusion of time effects. These are clearly important. z-scores vary from year to year in ways that are not picked up by the explanatory variables.

The impact of the cyclical variables changes according to how far ahead one is trying to forecast. In Table 4 we have explored how the cyclical variable change depending on whether they are forecasting 1, 2 or 3 years ahead. The other, bank specific, variables all retain just a single lag. This is of course a problem from a forecasting point of view as these variables are not forecastable. Hence column (2) is a better indicator of the model in that mode. As we discuss later, we have tried a variety of plausible explanations to take account of these annual fluctuations and it is surprising that they are not picked up by economy-wide variables.

As might be expected, the further ahead the forecast we weaker the explanation. Having the second lag on the main cyclical variables was our preferred specification in Table 3 as the relationship is not substantially changed from having just the one lag. However, when the lag is extended to three years the relationship becomes softer, although the household debt service ratio and market capitalisation both show clearly significant coefficients with the three year lag. Interestingly enough it is only with this longer lag that market capitalisation plays a role – higher values lead to banking problems three years later.

Table 4 Regression results using lagged observations of independent variables

	Lag 1	Lag 2	Lag 3
Constant	10.168***	10.318***	10.242***
	(15.50)	(14.05)	(12.63)
CI	-.00019***	-0.0016***	-0.0013***
(Cost to income)	(-4.99)	(-3.88)	(-2.71)
ECSTF	0.0015***	0.0015***	0.0013***
(Equity to customer & short term funding)	(4.28)	(3.58)	(3.00)
LAA	-0.0016**	-0.0012	-0.0013
(Liquid assets to total assets)	(-2.15)	(-1.39)	(-1.45)
LLPA	-0.0461***	-0.0477***	-0.0540***
(Loan loss provisions to total assets)	(-4.62)	(-4.56)	(-4.44)
NIIGR	-0.0003	-0.0004	-0.0002
(Non-interest income to gross revenues)	(-0.67)	(-0.80)	(-0.40)
NIM	0.0501***	0.0502***	0.0518***
(Net interest margin)	(4.26)	(3.65)	(3.39)
TA	-0.3128***	-0.3145***	-0.2872***
(Total assets)	(-10.35)	(-9.26)	(-7.86)
BC	-0.0083***	-0.0118***	-0.0218***
(Bank concentration)	(-3.28)	(-3.24)	(-4.50)
BC^2	0.0001***	0.0001***	0.0002***
(Bank concentration squared)	(2.98)	(3.03)	(4.08)
BSZ	-0.0128	-0.0392*	0.0080
(Banking sector z-score)	(-0.72)	(-1.80)	(0.37)
GDP_growth	0.0018	0.0062	-0.0127**
(Annual GDP growth)	(0.33)	(1.39)	(-2.53)
Inflation	-0.0089	-0.0354***	0.0011
(Annual change in CPI)	(-1.30)	(-2.74)	(0.11)
DSRNFC	0.0020	0.0001	0.0001
(Debt service ratio of non-financial corporations)	(1.18)	(0.07)	(0.04)
DSRHHS	-0.0242***	-0.0231***	-0.0242***
(Debt service ratio of households)	(-5.59)	(-5.14)	(-3.93)
MC_GDP	-0.0001	0.0003	-0.0019***
(Market capitalization to GDP)	(-0.13)	(0.81)	(-4.43)
M3_GDP	0.0022***	0.0029***	0.0017*
(Nominal M3 to GDP)	(2.80)	(3.48)	(1.78)
Financial cycle dummy	-0.0162*	-0.0192**	-0.0231**
	(-1.83)	(-2.20)	(-2.48)
Number of observations	10,915	9,385	8,005
R^2 (within)	0.2056	0.1912	0.1677

Notes: The bank-specific variables are lagged by 1 period in all specifications. The remaining independent variables are lagged by 1, 2, and 3 lags, as indicated in the column headings.

As we have quite a large sample we can check whether we are not constraining the analysis too much by treating all banks as being subject to the same model. If we look at the country fixed effects, for example, these are clearly significant in most cases. One might legitimately ask whether in fact all the coefficients are different by country rather than just the fixed effect. We do not have sufficient degrees of freedom to allow for that many interaction terms but we can consider whether the euro area banks perform differently from their counterparts outside the area. Given that the EU has created the Single Supervisory Mechanism, presided over by the ECB, for the euro are banks – although other may join – in 2014, this distinction may be of practical value from a decision-making point of view.

We therefore show estimates for the two regions of the EU in Table 5, each using the same specification as in Table 3 column (1). i.e. we do not attempt to optimise the lag structure in each case but simply test whether constraining the coefficients to be the same as in Table 3 is vindicated by the data. A Chow test suggests that the restriction is too harsh but the differences in the coefficients are relatively small. There are no striking sign or magnitude differences except for the financial cycle, although the euro area results are somewhat better determined, no doubt assisted by the greater sample size. In one sense the results are therefore expected as with a common monetary policy one might expect the euro area countries to be subject to different pressures from their non-euro counterparts, each of whom has a different policy, although, with its peg to the euro, one might expect Denmark to be similar to the euro. Similarly with their closer economic integration we might expect the parameters to be less affected by country variation.

Table 5 Euro area banks versus non-euro area banks

	(x1)	**(x2)**
Constant	9.944***	11.139***
	(11.14)	(9.16)
CI	-0.0015***	-0.0016*
(Cost to income)	(-3.04)	(-1.89)
ECSTF	0.0018***	0.0007
(Equity to customer & short term funding)	(3.93)	(0.94)
LAA	-0.0013	-0.0008
(Liquid assets to total assets)	(-1.29)	(-0.53)
LLPA	-0.0480***	-0.0469***
(Loan loss provisions to total assets)	(-3.70)	(-2.66)
NIIGR	-0.0006	-0.0006
(Non-interest income to gross revenues)	(-0.91)	(-0.64)
NIM	0.0429***	0.0578*
(Net interest margin)	(2.87)	(1.70)
TA	-0.2874***	-0.4100***
(Total assets)	(-7.00)	(-8.86)
BC	-0.0096**	0.0720
(Bank concentration)	(-2.09)	(1.52)
BC^2	0.0001*	-0.0006
(Bank concentration squared)	(1.86)	(-1.47)
BSZ	-0.0694***	-0.0472
(Banking sector z-score)	(-2.58)	(-0.40)
GDP_growth	0.0062	0.0128
(Annual GDP growth)	(1.12)	(1.16)
Inflation	-0.0421***	-0.0620
(Annual change in CPI)	(-2.81)	(-1.14)
DSRNFC	0.0056*	-0.0002
(Debt service ratio of non-financial corporations)	(1.91)	(-0.01)
DSRHHS	-0.0164**	-0.0557
(Debt service ratio of households)	(-2.25)	(-1.26)
MC_GDP	0.0008	-0.0011
(Market capitalization to GDP)	(1.52)	(-0.68)
M3_GDP	-0.0029	0.0063**
(Nominal M3 to GDP)	(-1.43)	(2.12)
Financial cycle dummy	-0.0281***	0.1052
	(-2.67)	(0.81)
Number of observations	7,704	1,681
R^2 (within)	0.1657	0.3499

In our main regressions thus far, size, as represented by total assets, has normally been highly significant but negative. We have therefore tried splitting the sample by size to see whether other factors lead to this perhaps surprising result. We divide the data into three categories as proposed in a paper of Basel Committee on Banking Supervision (2014)[7]. Table 6 reports the results for banks whose assets are less than EUR 1 billion (small), banks whose assets range from EUR 1 billion to EUR 100 billion (medium) and for banks whose assets exceed EUR 100 billion (large).

Table 9 Small-sized, medium-sized, and large-sized banks

	(small)	(medium)	(large)
Constant	12.813***	10.543***	10.227***
	(12.23)	(10.80)	(2.83)
CI	-0.0032***	-0.0011**	0.0020
(Cost to income)	(-4.34)	(-2.04)	(1.06)
ECSTF	0.0018**	0.0013***	-0.0058***
(Equity to customer & short term funding)	(2.54)	(3.17)	(-2.72)
LAA	-0.0015	-0.0012	0.0056
(Liquid assets to total assets)	(-1.19)	(-1.30)	(1.46)
LLPA	-0.0518***	-0.0415***	-0.0926
(Loan loss provisions to total assets)	(-4.04)	(-2.71)	(-0.74)
NIIGR	-0.0004	0.0002	0.0025
(Non-interest income to gross revenues)	(-0.44)	(0.23)	(1.33)
NIM	-0.0029	0.0781***	0.2657***
(Net interest margin)	(-0.21)	(4.65)	(3.09)
TA	-0.4636***	-0.3146***	-0.2809**
(Total assets)	(-8.75)	(-7.07)	(-2.11)
BC	-0.0084	-0.0189***	-0.0558***
(Bank concentration)	(-1.53)	(-4.02)	(-3.38)
BC^2	0.0001	0.0002***	0.0004***
(Bank concentration squared)	(1.43)	(3.57)	(2.92)
BSZ	-0.0584*	0.0189	0.0504
(Banking sector z-score)	(-1.68)	(0.80)	(0.57)
GDP_growth	0.0167**	0.0001	-0.0003
(Annual GDP growth)	(2.18)	(0.15)	(-0.02)
Inflation	0.0084	0.0172	0.0162
(Annual change in CPI)	(0.61)	(1.40)	(0.41)
DSRNFC	-0.0011	0.0006	-0.0071
(Debt service ratio of non-financial corporations)	(-0.32)	(0.24)	(-1.21)
DSRHHS	-0.0248***	-0.0169***	0.0446
(Debt service ratio of households)	(-2.87)	(-2.96)	(1.52)
MC_GDP	0.0001	0.0001	-0.0003
(Market capitalization to GDP)	(0.14)	(0.11)	(-0.18)
M3_GDP	0.0017	0.0017	0.0035
(Nominal M3 to GDP)	(1.36)	(1.55)	(1.06)
Financial cycle dummy	-0.0025	-0.0332***	-0.0818*
	(-0.15)	(-3.37)	(-1.76)
Number of observations	2,910	5,490	523
R^2 (within)	0.2754	0.2398	0.3539

While signs vary little over the three groups, magnitudes of coefficients are sometimes very different. For example efficiency in the sense of cost/income only seems important for small banks. Cyclical factors are most important for the medium-sized banks, while the phase of the financial cycle does not seem important for small banks. Within the size categories total assets retain their negative sign and the variable is significant across all sizes of banks. z-

[7] http://www.bis.org/bcbs/publ/d300.pdf.

scores are rather better explained in the case of the large banks than the others. As the Chow test shows, it is clearly not warranted to restrict coefficients to be the same for all three groups.

Finally, instead of simply seeing whether z-scores were lower in the down phase of the cycle we have split estimation between the down and up phases. Here the results are striking Table 7). Many of the variables change sign and magnitudes can be substantially different. It is clear that behaviour is not symmetric across the cycle but varies considerably. We only have enough data to estimate a simple split in regimes rather than a smooth transition model (Mayes and Virén, 2011). However, this is a case where the transition is likely to be rapid when the economy switches from growth to contraction and the problems are realised. It is at the other end of the transition where a sharp switch is less plausible. Recoveries in confidence tend to emerge only slowly and even if one has a Minskyan view of the way speculative bubbles build up, the process is progressive and involves a series of stages where risk-taking builds (Minsky, 1986).

As part of the robustness testing we have checked whether our error structures are too simplistic. Table B.1 in Appendix B reports GLS regression results conditioning on country effects on whether the banks were located in the euro area, on whether the banks were listed and on banks' size (results available on request).

These results show that there are significant country effects. The baseline country is Germany. Apart from banks in France all the banks in other countries have significantly lower z-scores compared to Germany. The z-score of the euro area banks is significantly higher compared to that of the non-euro area banks. Although listed banks have lower z-score compared to the non-listed banks, the result is not significant. The z-scores of medium and small banks are significantly lower compared to the z-scores of the small banks. Finally, in all specifications, the coefficient estimate of the financial cycle dummy variable is negative and statistically significant.

Table 7 Downside financial cycle versus upside financial cycle

	(downside)	(upside)
Constant	9.223***	10.328***
	(5.41)	(8.28)
CI	0.0009	-0.0018**
(Cost to income)	(0.97)	(-2.35)
ECSTF	0.0015**	0.0004
(Equity to customer & short term funding)	(1.98)	(0.80)
LAA	0.0006	-0.0003
(Liquid assets to total assets)	(0.40)	(-0.24)
LLPA	-0.0237	-0.0241
(Loan loss provisions to total assets)	(-1.16)	(-1.32)
NIIGR	0.0009	-0.0013
(Non-interest income to gross revenues)	(0.81)	(-1.58)
NIM	0.0768***	-0.0159
(Net interest margin)	(2.79)	(-0.80)
TA	-0.2131***	-.03165***
(Total assets)	(-3.35)	(-5.96)
BC	-0.0483**	-6.81e-06
(Bank concentration)	(-2.00)	(-0.00)
BC^2	0.0003*	-0.0001
(Bank concentration squared)	(1.77)	(-0.93)
BSZ	0.0796	-0.1889***
(Banking sector z-score)	(1.18)	(-2.61)
GDP_growth	0.0330**	0.0081
(Annual GDP growth)	(2.40)	(1.23)
Inflation	-0.1489***	-0.0098
(Annual change in CPI)	(-4.40)	(-0.42)
DSRNFC	0.0113	-0.0101*
(Debt service ratio of non-financial corporations)	(1.21)	(-1.64)
DSRHHS	-0.0520***	-0.0212
(Debt service ratio of households)	(-2.64)	(-1.09)
MC_GDP	-0.0033	0.0012
(Market capitalization to GDP)	(-1.45)	(0.67)
M3_GDP	0.0105***	0.0109
(Nominal M3 to GDP)	(4.07)	(1.45)
Number of observations	3,644	3,253
R^2 (within)	0.1028	0.1558

5 Conclusions

Our concern in this paper is to explore whether it is possible to identify problems relatively early on so that corrective measures can be applied before problems reach crisis proportions. We are able to show for a large sample of European banks, over the period 1999-2014, that it is possible to provide useful forecasts of weakness and potential problems at least a year ahead. Four main factors explain the weakness: bank specific variables, which a related to the well-known CAMELS variables that have been widely used to measure bank quality, banking system structure, variables relating to the economic cycle and finally variables relating to the financial cycle. We show that there is clear variation among banks according to their size and whether or not they are listed. There is also a difference in the EU between euro area and non-euro area countries, although the sources of this are difficult to ascertain. But most importantly we can show that the determination of weakness varies strongly with respect to the phase of the financial cycle. Banks become asymmetrically weak in the down phase.

While this may seem rather straightforward, the fact that we can identify this potential weakness up to two years ahead provides some hope for the usefulness of this approach as an early warning system. Our analysis is based purely on published data by BankScope and the IMF. Supervisors have access to more detail and confidential data but above all the banks' management has the best source of information. Since in the early phase of trying to right problems in banks – the recovery phase to use the common terminology – the responsibility for action lies with the bank itself, encouraged by the supervisor, that privileged access is just what is needed. The fact that outsiders can also see the emerging difficulties will provide a further incentive to the bank management to act early. That said, history suggests that despite the early warning signals both bank management and supervisors tend to delay action (Garcia, 2012). In part this may be that they feel they can explain away the tensions, perhaps in a single bank equivalent to Reinhart and Rogoff's (2009) suggestion that banking crises occur despite the signals because people convince themselves that 'this time is different'.

Appendix A

Table A.1 Allocation of banks by country

Country	Frequency of banks	Cumulative Frequency
Austria	194	194
Belgium	73	267
Germany	201	468
Denmark	138	606
Spain	227	833
Finland	43	876
France	302	1178
Greece	29	1479
Ireland	55	1534
Italy	316	1850
Luxembourg	141	1991
Netherlands	81	2072
Portugal	60	2132
Sweden	107	2239
United Kingdom	272	1450

Table A.2 Types of banks

Entity	Frequency	Cumulative Frequency
Branch location	5	5
Controlled subs.	834	839
GUO	370	1209
Independent co	208	1417
Single location	726	2143
Unknown	96	2239

Appendix B

Table B.1 Country effects

	Coefficient	z-statistic
Constant	8.329***	19.95
CI (Cost to income)	-0.0017***	-4.22
ECSTF (Equity to customer & short term funding)	0.0018***	4.77
LAA (Liquid assets to total assets)	-0.0017**	-2.31
LLPA (Loan loss provisions to total assets)	-0.0569***	-5.51
NIIGR (Non-interest income to gross revenues)	-0.0007	-1.35
NIM (Net interest margin)	0.0542***	4.17
TA (Total assets)	-0.1888***	-10.69
BC (Bank concentration)	-0.0126***	-3.48
BC^2 (Bank concentration squared)	0.0001***	3.33
BSZ (Banking sector z-score)	-0.0393*	-1.78
GDP_growth (Annual GDP growth)	0.0054	1.19
Inflation (Annual change in CPI)	-0.0342***	-2.62
DSRNFC (Debt service ratio of non-financial corporations)	-0.0010	-0.49
DSRHHS (Debt service ratio of households)	-0.0245***	-5.34
MC_GDP (Market capitalization to GDP)	0.0001	0.09
M3_GDP (Nominal M3 to GDP)	0.0032***	3.73
Financial cycle dummy	-0.0208**	0.017
Belgium	-1.390***	-6.80
Austria	-0.983***	-7.98
Denmark	-1.305***	-9.25
Spain	-0.629***	-4.91
Finland	-0.737***	-3.34
France	-0.198	-1.64
UK	-0.331**	-2.49
Greece	-2.119***	-12
Ireland	-1.026***	-3.91
Italy	-0.739***	-6.73
Luxembourg	-0.854***	-0.44
Netherlands	-0.872***	-4.72
Portugal	-1.076***	-5.52
Sweden	-1.265***	-9.51
Number of observations		9,385
R^2 (within)		0.1811

Baseline country: Germany

GLS regression results

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