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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 sector and macroeconomic variables to which we add financial cycle indicators. Testing this model on an unbalanced panel of 2,239 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. This paper explores whether it is possible to identify bank problems relatively early on so that corrective measures can be applied before problems reach crisis proportions. In their analysis of 800 years of such crises, Reinhart and Rogoff (2009) illustrate that, 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. In this paper, we focus on 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.

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A striking feature of the global financial crisis (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 macroeconomic, banking sector, 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, we seek to expand that analysis by adding financial cycle indicators to the traditional model. 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 macroprudential regulators (ESRB, 2014).

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 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.

Overall, we find that financial indicators can predict one, two and even three years ahead. Furthermore, we find behaviour is asymmetric, depending on the phase of the financial cycle. Of course there is always a chance that 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 obtained from 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 model.

The present study is exploratory, which uses data from EU-15. We begin in Section 1 by developing the context for our study 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 resent GFC have refocused attention on both reducing the chance of future crises and reducing the costs of any such crises that do occur.[2] Action has taken place on a number of fronts. For example, under Basel 3, capital buffers and liquidity provisions have increased to enhance banks' resilience to various shocks. Also, a wide range of tools have been implemented such as bailing in creditors rather than using taxpayer funds to absorb losses and resolve large banks.

The problem of banks being international but the authorities that control them being national are being addressed through international institutions. For example, Financial Stability Board (FSB) has recommended key attributes with recovery and resolution among them (see FSB, 2011). 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. In the European context, this problem is dealt with the creation of a banking union and its associated institutions and mechanisms such as the Single Supervisory Mechanism (SSM) and the Single Resolution Mechanism (SRM).[3]

Regarding the structure of banking groups, various measures have been implemented in order to separate the risky banking activities from the more traditional ones. The 'Volcker rule' in the US and similar measures in the UK, France, Germany are some examples. At the EU level, no such measures have been applied yet despite the Liikanen Report (for more details, see Lehmann, 2014).

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 suggest that the benefits greatly outweigh the costs (European Commission, 2012; RBNZ, 2012). For example, 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. Moreover, its bail in scheme – labelled Open Bank Resolution (OBR) – will be rather unlikely in practice. This is because

[2] 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, Dell'Ariccia et al. 2008).
[3] For more information refer to Regulation (EU) No 1022/2013 and Regulation (EU) No 806/2014.

under OBR, the shareholders and management lose control of the bank and thus should be incentivized to run the bank more prudently.

Within this context, this paper touches on the ability to detect problems in individual banks 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.[4] 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 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. (2015) 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 here is of very low cost.

2 The Model

Our basic approach is straightforward. Banking problems are a function of bank-specific, banking sector, macroeconomic and macrofinancial variables. In this section, we explain our choice of those variables, including our measure of banking problems, and the model 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.

Dependent variable: binary versus continuous

Most previous research tends to use some form of logit or probit model to explain banking failures or distress by taking the occurrence of such failure or distress as their dependent variable. More specifically, this variable equals 1 in the case of a crisis, failure or distress and 0 otherwise (see for example, Laeven and Valencia, 2013). Unlike in the US, there have not been many clear bank failures in Europe. This creates a difficulty in using a binary variable in our case as we would have a very thin data set for explaining failure. However, we are not seeking simply to explain failure but also to identify when banks are getting into difficulty so

[4] The GFC 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. This is addressed by the development of macroprudential policies, which is not covered in the present paper.

early action could take place. Thus, using a continuous variable that proxies for bank distress would be more appropriate. The two most widely used continuous indicators are the z-scores and distance to default.

In this paper, we focus on z-scores, because this permits us to use a larger sample, and leave distance to default for subsequent study. z-scores are accounting-based measures, obtained from balance sheet and income statements of the banks and financial institutions under investigation, which can be applied to both listed and unlisted firms.[5] In essence, a z-score shows the number of standard deviations that a bank's rate of return on assets can fall in a single period before it becomes insolvent. Thus, a higher z-score signals a lower probability of bank insolvency (Bertay et al., 2013).[6]

The z-score can be calculated as follows:

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

where $ROA_{i,t}$ is the return on assets of bank i 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).[7] Even with a z-score we cannot get away from problems from a skewed distribution of the dependent variable. In line with Laeven and Levine (2009), Demirguc-Kunt and Huizinga (2010), and Houston et al. (2010), we take the natural logarithm of the z-score to offset this.

Independent variables

We build on the considerable literature published on early warning indicators to identify the variables that help predict vulnerabilities in banks and the financial system.[8] Explanatory variables fall into five main categories (see columns 1 and 2 of Table 1 for variable descriptions):

- Bank-specific (drawn from accounting data)
- Banking sector
- Macroeconomic

[5] Distance to default is usable only for listed firms as it requires market price data.
[6] z-scores are extensively used in the literature. See for example, Boyd et al. (1993), Boyd et al. (2006), Schaeck and Cihak (2010), and Beck et al. (2013).
[7] In common with the literature we also explore a three-year window but this tends to be unstable.
[8] Yucel (2011) and Mayes and Stremmel (2014) provide an extensive literature review on early warning models.

- Macrofinancial
- Financial cycle phase.

There are relatively few studies that look at banking distress in Europe for us to build on (see for example, Poghosyan and Čihák, 2009), although the European Central Bank (ECB) studies listed in MARS report provide a wealth of suggestions about indicators for the banking system as a whole (ECB, 2014).

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, although our choice is constrained by data availability. In general terms, these variables run across the six categories thought relevant by the Federal Deposit Insurance Corporation (FDIC) in its own monitoring of banks in the US, which goes by the acronym of CAMELS (FDIC, 2015); where the components stand for: 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. In our model, we use the following bank-specific variables: equity to customer and short term funding ratio (C); loan loss provisions to total assets ratio (A); cost to income ratio and net interest margin (E); liquid assets to total assets ratio (L).[9]

Banking sector variables

Work on issues of banking market 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. The authors 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

[9] As part of the robustness testing we experimented with a much wider range of similar variables available in Bankscope.

accounted for by state owned banks. 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 a banking market concentration index.[10] Additionally, we include the banking sector z-score in our regression analysis.

Macroeconomic variables

There is extensive evidence that adverse macroeconomic conditions can lead to banking problems (Borio and Drehmann, 2009). Demirgüc-Kunt and Detragiache (2005), for example, consider GDP growth and inflation as proxies to control for business cycle effects; while Männasoo and Mayes (2009) also include interest rates, the change in the exchange rate and the ratio of private lending to GDP. In our exploratory analysis, we use GDP growth and inflation as the addition of further such variables seems to add little to the explanation.

Macrofinancial 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 GFC (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 macrofinancial indicators do not.[11]

There are two obvious groups of macrofinancial 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,

[10] 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.

[11] Stremmel (2015) shows that the periodicity of macroeconomic and financial cycles is clearly different in Europe over the last 30-40 years.

particularly real estate. Barrell et al. (2010), for example, use property prices in their analysis to predict systemic banking crises.[12]

While some authors focus on just one group of variables, others, 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 their interaction 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. 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.[13]

In our model, we incorporate the following macrofinancial variables: debt service ratio of non-financial corporations; debt service ratio of households; market capitalization to GDP ratio; nominal M3 money supply aggregate to GDP ratio. The next sub-section explains the calculation of the financial cycle metric based on which the expansion and contraction phases of the financial cycle, respectively, are identified.

Financial cycle phase

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. Because the finance sector is prone to overshooting and asset prices reflect anticipated returns over the future life of the asset, where the actual returns are unknown beforehand, such prices can vary widely for longer term assets on the basis of quite limited news. We thus can get considerable volatility, which helpful in a forecasting context. Moreover, markets 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. We thus get very sharp changes in sentiment, which alter how markets behave

Financial cycles are 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

[12] Part of the problem is simply to distinguish cyclical from structural factors (Stremmel and Zsámboki, 2015).
[13] Detken et al. (2014) provide the most comprehensive analysis of how to combine measures.

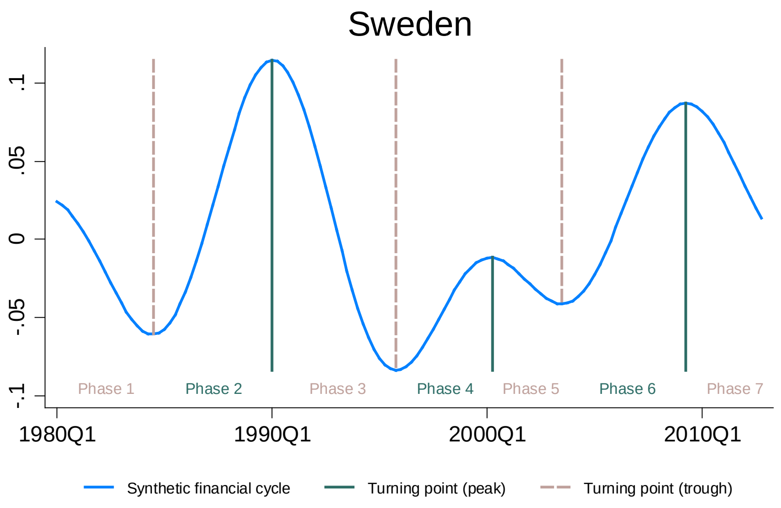
and longer recovery periods. Recent evidence has shown that financial cycle peaks tend to be associated with systemic banking distress and financial cycles are helpful in the timely detection of distress in the financial system (Borio, 2014; Stremmel, 2015). Further, Aizenman et al. (2013) show that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

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.[14] 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-to-income ratio.

We are therefore able to approach whether financial cycles provide additional information about impending banking distress from two directions. First of all we simply include the financial cycle indicators themselves to add to the ability to explain but, secondly, and more importantly, we distinguish behaviour in the up phase of the cycle from the down phase: when it is moving down and when it is moving up. 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 as banks try to increase their liquidity. Thus, there is 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. The financial cycle dummy variable in our analysis takes the value of 1 when the cycle moves down and 0 otherwise.

[14] Babecký et al. (2012), in their examination of the stylized facts of banking, debt and currency crises, find that growth of 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.

Figure 1 Financial Cycles



Based on: Stremmel (2015)

3 Sample and Descriptive Statistics

Our sample comprises annual data on 2,239 banks in the EU-15 countries over the period 1999-2014. 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 European banks are obtained from Bankscope; data on macroeconomic variables are obtained from International Financial Statistics (IFS) of IMF; banking sector and macrofinancial data are obtained from the Bank for International Settlements (BIS).

Table 1 describes the variables with their mnemonics and provides their descriptive statistics, while Table 2 shows the correlations between the various independent variables. As expected there is inevitably some overlap among the bank-specific and macrofinancial variables (see 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.

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 ratio	64.23	63.48	24.98	7.24	182.50
ECSTF	Equity to customer & short term funding ratio	18.33	9.50	39.26	1.06	319.77
LAA	Liquid assets to total assets ratio	24.34	16.29	22.83	0.32	97.16
LLPA	Loan loss provisions to total assets ratio	0.42	0.23	0.69	-0.54	4.27
NIIGR	Non-interest income to gross revenues ratio	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 (Herfindahl Index)	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 (%)	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 ratio	72.60	65.59	42.40	13.48	210.51
M3_GDP	Nominal M3 to GDP ratio	129.28	90.16	160.17	42.78	831.33

Table 2 Correlation matrix of independent 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

***, **, * denote significance at the 1%, 5% and 10% levels respectively

4 Regression analysis

We use a fixed-effects panel data model with robust errors, 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. 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. Total assets (TA) and the banking sector z-score (BSZ), which are not expressed in percentages or ratios, undergo logarithmic transformation to reduce any skewness and heteroscedasticity problems that might occur in the regression analysis as in Benston and Hagerman (1974).

For our model to be useful it needs to forecast, so, all the explanatory variables are lagged. This also mitigates reverse causality concerns as in Saunders et al. (2014). 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 (Uhde and Heimeshoff, 2009; Drehmann and Julius, 2014). Thus, we explore specifications where we lag our macroeconomic and macrofinancial variables by longer that one year. 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.[15]

Results

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

[15] 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.

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 not 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 its loan portfolio is impaired. Clearly, if the expected loan losses were similar across banks, then having greater provisions would indicate a safer bank. Net interest margin is also positive, indicating a more profitable and hence stronger bank.

Turning to the banking sector variables, 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. As for the macroeconomic variables in the full model, both variables have the expected sign but only inflation is statistically significant.

The macrofinancial 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 below 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.

As discussed in Section 2, the financial cycle variable is composed of weights on the main factors we consider: credit-to-GDP ratio, credit growth and house-prices-to-income ratio. Our suggestion is that z-scores are affected by the phase of the cycle. We see that in the down phase z-scores are lower – given the values of all the other variables in the model. One 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 (see Table 6).

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

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
Number of banks	1,521	1,521	1,521	1,521	1,521	1,521
R^2 (within)	0.1912	0.1573	0.1564	0.1227	0.1109	0.1029

Note: In all specifications the bank-specific variables, banking sector variables, and debt to service ratio are lagged by one period while the remaining variables are lagged by two periods. Specification (2) differs from specification (1) in that the time effects are removed.

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.

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.

Robustness

The impact of the cyclical variables changes according to how far ahead one is trying to forecast. In Table 4 we explore how the cyclical variable changes depending on whether we are forecasting one, two or three years ahead. Bank-specific, banking sector and debt to service ratio variables all retain just a single lag. 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.

Table 4 Various lags 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
Number of banks	1,664	1,521	1,393
R^2 (within)	0.2056	0.1912	0.1677

Note: The bank-specific variables, banking sector variables, and debt to service ratio are lagged by one period in all specifications. The remaining independent variables are lagged by one, two, and three lags, as indicated in the column headings.

As might be expected, the further ahead the forecast the 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. Interestingly enough, it is only with this longer lag that market capitalisation plays a role – higher values lead to banking problems three years later.

As we have quite a large sample we can check whether we are constraining the analysis too much by treating all banks as being subject to the same model. Next, we consider whether the euro area banks perform differently from their counterparts outside the area. Given that the EU has created the SSM, presided over by the ECB, mainly for the euro area banks, 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 the first two columns of Table 5, each using the same specification as in Table 3 column (1).[16] 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.

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). The last three columns of Table 5 report 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).

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-

[16] 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.

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.

Table 5 Robustness of different categories of banks

	euro vs. non-euro		size		
	(euro area)	**(non-euro area)**	**(small)**	**(medium)**	**(large)**
Constant	9.944***	11.139***	12.813***	10.543***	10.227***
	(11.14)	(9.16)	(12.23)	(10.80)	(2.83)
CI	-0.0015***	-0.0016*	-0.0032***	-0.0011**	0.0020
(Cost to income)	(-3.04)	(-1.89)	(-4.34)	(-2.04)	(1.06)
ECSTF	0.0018***	0.0007	0.0018**	0.0013***	-0.0058***
(Equity to customer & short term funding)	(3.93)	(0.94)	(2.54)	(3.17)	(-2.72)
LAA	-0.0013	-0.0008	-0.0015	-0.0012	0.0056
(Liquid assets to total assets)	(-1.29)	(-0.53)	(-1.19)	(-1.30)	(1.46)
LLPA	-0.0480***	-0.0469***	-0.0518***	-0.0415***	-0.0926
(Loan loss provisions to total assets)	(-3.70)	(-2.66)	(-4.04)	(-2.71)	(-0.74)
NIIGR	-0.0006	-0.0006	-0.0004	0.0002	0.0025
(Non-interest income to gross revenues)	(-0.91)	(-0.64)	(-0.44)	(0.23)	(1.33)
NIM	0.0429***	0.0578*	-0.0029	0.0781***	0.2657***
(Net interest margin)	(2.87)	(1.70)	(-0.21)	(4.65)	(3.09)
TA	-0.2874***	-0.4100***	-0.4636***	-0.3146***	-0.2809**
(Total assets)	(-7.00)	(-8.86)	(-8.75)	(-7.07)	(-2.11)
BC	-0.0096**	0.0720	-0.0084	-0.0189***	-0.0558***
(Bank concentration)	(-2.09)	(1.52)	(-1.53)	(-4.02)	(-3.38)
BC^2	0.0001*	-0.0006	0.0001	0.0002***	0.0004***
(Bank concentration squared)	(1.86)	(-1.47)	(1.43)	(3.57)	(2.92)
BSZ	-0.0694***	-0.0472	-0.0584*	0.0189	0.0504
(Banking sector z-score)	(-2.58)	(-0.40)	(-1.68)	(0.80)	(0.57)
GDP_growth	0.0062	0.0128	0.0167**	0.0001	-0.0003
(Annual GDP growth)	(1.12)	(1.16)	(2.18)	(0.15)	(-0.02)
Inflation	-0.0421***	-0.0620	0.0084	0.0172	0.0162
(Annual change in CPI)	(-2.81)	(-1.14)	(0.61)	(1.40)	(0.41)
DSRNFC	0.0056*	-0.0002	-0.0011	0.0006	-0.0071
(Debt service ratio of non-financial corporations)	(1.91)	(-0.01)	(-0.32)	(0.24)	(-1.21)
DSRHHS	-0.0164**	-0.0557	-0.0248***	-0.0169***	0.0446
(Debt service ratio of households)	(-2.25)	(-1.26)	(-2.87)	(-2.96)	(1.52)
MC_GDP	0.0008	-0.0011	0.0001	0.0001	-0.0003
(Market capitalization to GDP)	(1.52)	(-0.68)	(0.14)	(0.11)	(-0.18)
M3_GDP	-0.0029	0.0063**	0.0017	0.0017	0.0035
(Nominal M3 to GDP)	(-1.43)	(2.12)	(1.36)	(1.55)	(1.06)
Financial cycle dummy	-0.0281***	0.1052	-0.0025	-0.0332***	-0.0818*
	(-2.67)	(0.81)	(-0.15)	(-3.37)	(-1.76)
Number of observations	7,704	1,681	2,910	5,490	523
Number of banks	1,249	272	506	982	102
R^2 (within)	0.1657	0.3499	0.2754	0.2398	0.3539

Finally, instead of simply seeing whether z-scores were lower in the down phase of the cycle we have split estimation between the down (contraction) and up (expansion) phases. Here the results are striking (see Table 6). 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 (see for example, 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 increases (Minsky, 1986).[17]

Table 6 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
Number of banks	1,200	1,115
R^2 (within)	0.1028	0.1558

5 Conclusions

This paper explores whether problems in individual banks can be detected early enough and resolved before they reach crisis proportions. Examining the EU-15 banks over the period 1999-2014, we find that financial cycle dynamics can provide additional useful forecasts of weakness and potential problems in banks at least a year ahead. We also show that there is clear variation among banks according to their size and whether they are located in the euro

[17] Additional tests (not reported here for brevity) show that there are significant country effects. All the banks in other countries, with the exception of France where the result is marginally significant, have significantly lower z-scores compared to Germany, which was chosen as the baseline country. Also, the z-score of the euro area banks is significantly higher compared to that of the non-euro area banks; while the z-scores of medium and large banks are significantly lower compared to the z-scores of the small banks. Finally, the coefficient estimate of the financial cycle dummy variable remains negative and statistically significant.

area or not, 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 data from Bankscope, IMF, and BIS. 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 equivalent to Reinhart and Rogoff's (2009) suggestion that banking crises occur despite the signals because people convince themselves that 'this time is different'.

For further research, our steps would be to include more countries in the analysis, use alternative measures of bank distress and employ alternative econometric approaches, to shed additional light on the topic.

References

Aizenman, J., Pinto, B. and Sushko, V. (2013). Financial sector ups and downs and the real sector in the open economy: Up by the stairs, down by the parachute, *Emerging Markets Review 16*, 1–30.

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K., and Vašíček, B. (2012). Banking, debt, and currency crises early warning indicators for developed countries, ECB working paper series, No 1485 / October.

Barrell, R., Davis, E.P., Karim, D., and Liadze, I. (2010). Bank regulation, property prices and early warning systems for banking crises in OECD countries, *Journal of Banking & Finance 34*, 2255–2264.

Basel Committee on Banking Supervision (2014). Regulatory Consistency Assessment Programme (RCAP), Assessment of Basel III regulations – European Union, available at http://www.bis.org/bcbs/publ/d300.pdf (last accessed 12 November 2015).

Beck, T., De Jonghe, O., and Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity, *Journal of Financial Intermediation*, *22*(2), 218–244.

Benston, G.J., & Hagerman, R. L. (1974). Determinants of Bid-Asked Spreads in the Over-the-Counter Market. *Journal of Financial Economics*, *1*(4), 353–364.

Bertay, A.C., Demirgüç-Kunt, A., and Huizinga, H. (2013). Do we need big banks? Evidence on performance, strategy and market discipline, *Journal of Financial Intermediation*, *22*(4), 532–558.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance 45*, 182–198.

Borio, C. and Drehmann, M. (2009). Assessing the risk of banking crises – revisited, *Bank for International Settlements Quarterly Review*, March, 29–46.

Boyd, J. H., Graham, S. L., and Hewitt, R. S. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of failure, *Journal of Banking and Finance 17*, 43–63.

Boyd, J.H., De Nicolo, G., Jalal, A.M. (2006). Bank risk-taking and competition revisited: new theory and new evidence. IMF Working Paper No. 06/297.

Dell'Ariccia, G., Detragiache, E. and Rajan, R. (2008). The real effects of banking crises. *Journal of Financial Intermediation*, *17*, 89–112.

Demirgüc-Kunt, A. and Detragiache, E. (2005). Cross-country empirical studies of systemic bank distress: A survey. IMF Working Paper No. WP/05/96.

Demirguc-Kunt, A. and Huizinga, H. (2010). Bank activity and funding strategies: the impact on risk and returns, *J. Finan. Econ*. *98*(3), 626–650.

Detken, C. and 14 others (2014) Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options, European Systemic Risk Board Occasional Paper no.5, available at https://www.esrb.europa.eu/pub/pdf/occasional/20140630_occasional_paper_5.pdf?12806293e038df2398ec91fccaf5c6ac (last accessed 29 October 2015).

Drehmann, M. and Juselius, M (2014). evaluating early warning indicators of banking crises: satisfying policy requirements, *International Journal of Forecasting*, *30*(3), 759–780.

Engle R., Jondeau, E. and Rockinger, M. (2015). Systemic risk in Europe, *Review of Finance*, *19(1)*, 145–190.

European Central Bank (2014) Report on the macro-prudential research network (MARS) available at http://www.ecb.europa.eu/events/pdf/conferences/140623/MaRs_report.pdf (last accessed 29 October 2015).

European Commission (2012). Commission staff working document on impact assessment accompanying the document proposal for a directive of the European Parliament and of the Council establishing a framework for the recovery and resolution of credit institutions and investment firms and amending Council Directives 77/91/EEC and 82/891/EC, Directives 2001/24/EC, 2002/47/EC, 2004/25/EC, 2005/56/EC, 2007/36/EC and 2011/35/EC and Regulation (EU) No 1093/2010, available at http://ec.europa.eu/internal_market/bank/docs/crisis-management/2012_eu_framework/impact_ass_en.pdf (last accessed 31 October 2014).

European Systemic Risk Board (2014). The ESRB handbook on operationalising macro-prudential policy in the banking sector, available at https://www.esrb.europa.eu/pub/pdf/other/140303_esrb_handbook.pdf (last accessed 13 March 2015).

Federal Deposit Insurance Corporation (FDIC) (2015) *Risk Management Manual of Examination Policies*, available at https://www.fdic.gov/regulations/safety/manual/ (last accessed 25 August 2015).

Financial Stability Board (2011). Key Attributes of Effective Resolution Regimes for Financial Institutions, available at http://www.financialstabilityboard.org/publications/r_111104cc.pdf (last accessed 30 October 2014).

Garcia, G.G.H. (2012). Missing the red flags. In: D.G. Mayes and G.E. Wood (eds.) Improving the Governance of the Financial Sector, ch. 10. Abingdon, UK: Routledge.

Houston, J.F., Lin, C., Lin, P., and Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking, *Journal of Financial Economics*, *96*(3), 485–512.

Köhler, M. (2012). Which banks are more risky? The impact of loan growth and business model on bank risk-taking, Discussion Paper Deutsche Bundesbank No 33/2012.

Laeven, L. and Levine, R. (2009). Bank governance, regulation and risk taking, *Journal of Financial Economics*, *93*(2), 259–275.

Laeven, L. and Valencia, F. (2013), Systemic banking crises database, *IMF Economic Review*, *61*, 225–270.

Lehmann, M. (2014). Volcker Rule, Ring-Fencing or Separation of Bank Activities: Comparison of Structural Reform Acts Around the World, LSE Law, Society and Economy Working Paper 25/2014.

Männasoo, K.; and Mayes, D. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking & Finance*, *33*(2), 244–253.

Mayes, D.G. and Virén, M. (2011) *Asymmetry and Aggregation in the EU*, Basingstoke: Palgrave-Macmillan.

Minsky, H. (1986). *Stabilizing an Unstable Economy*, New Haven, CN: Yale University Press.

Poghosyan, T. and Cihak, M. (2009). Distress in European banks: an analysis based on new data, IMF Working Paper WP/09/9.

Regulation (EU) No 1022/2013 of the European parliament and of the council of 22 October 2013 amending Regulation (EU) No 1093/2010 establishing a European Supervisory Authority (European Banking Authority) as regards the conferral of specific tasks on the European Central Bank pursuant to Council Regulation (EU) No 1024/2013, available at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:287:0005:0014:EN:PDF (last accessed 12 November 2015).

Regulation (EU) No 806/2014 of the European Parliament and of the Council establishing uniform rules and a uniform procedure for the resolution of credit institutions and certain investment firms in the framework of a Single Resolution Mechanism and a Single Resolution Fund and amending Regulation (EU) No 1093/2010, available at http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014R0806&from=EN (last accessed 12 November 2015).

Reinhart, C.M. and Rogoff K.S (2009). *This Time is Different: Eight Centuries of Financial Folly*, Princeton: Princeton University Press.

Reserve Bank of New Zealand (2012). 'Regulatory impact assessment of pre-positioning for Open Bank Resolution', available at http://www.rbnz.govt.nz/regulation_and_supervision/banks/policy/5014272.pdf (last accessed 20 October 2014).

Saunders, A., Schmid, M., and Walter, I. (2014). Non-interest income and bank performance: is banks' increased reliance on non-interest income bad?, University of St. Gallen, School of Finance Research Paper No. 2014/17.

Schaeck, K. and Cihák, M. (2010). Competition, efficiency, and soundness in banking: an industrial organization perspective, European Banking Center, Discussion Paper No. 2010-20S.

Stremmel, H. (2015). Capturing the financial cycle in Europe, *ECB Working Paper Series* No. 1811/June.

Stremmel, H. and Zsámboki, B. (2015) The relationship between structural and cyclical features of the EU financial sector, ECB Working Paper no 1812.

Uhde, A. and Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: empirical evidence, *Journal of Banking and Finance, 33*, 1299–1311.

Yucel, E. (2011). A review and bibliography of early warning models, MPRA Paper No. 32893.