The United Kingdom's small banks' crisis of the early 1990s: what were the leading indicators of failure?

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The views expressed are those of the author and do not necessarily reflect those of the Bank of England. The author is indebted to Glenn Hoggarth for his help and guidance. Patricia Jackson, Fiona Mann, William Perraudin, Victoria Saporta, Paul Tucker, Geoffrey Wood and participants at a seminar at the Bank of England and a workshop on early warning systems for member institutions of the Basel Committee on Banking Supervision are thanked for helpful comments. Joe Thomas is also thanked for his participation in part of the project and in particular for contributing to the early econometric work.

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The Bank of England's working paper series is externally refereed.

Bank of England 2001
ISSN 1368-5562

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Abstract

The announcement of BCCI's closure on 5 July 1991 rapidly accelerated the withdrawal of wholesale funds from small and medium-sized UK banks. Within three years, a quarter of the banks in this sector, had in some sense, failed. This study employs a logit model to analyse at two points prior to the crisis the distinct characteristics of the banks that failed compared with those that survived. Perhaps not surprisingly, a number of measures of bank weakness — low loan growth, poor profitability and illiquidity — are found to be good short-term predictors of failure, as are a high dependence on net interest income and *low* leverage. The best longer-term leading indicator of future failure, however, is *rapid* loan growth at the peak of the previous boom.

Key words: Bank failure, prediction.
JEL classification: G21, G28, G33.

Summary

Bank failure has fortunately been a rare event in the United Kingdom. Even more infrequent has been the simultaneous failure of a number of banks that potentially threatens the stability of the financial system. This study uses as a backdrop the period, known as the small banks' crisis of the early 1990s, when failure was last widespread and the system faced a potentially systemic threat. It was also the most recent occasion on which the Bank of England provided emergency liquidity support to UK banks.

Using a logit model this study examines the balance sheet characteristics of the small and medium-sized UK banks at two points prior to the crisis period to see whether the banks that would go on to fail had any distinctive features compared with those that would survive. Its goal is to identify leading indicators of failure. This may assist the Bank of England and the Financial Services Authority (FSA) in crisis prevention policy prescriptions before a future crisis has had a chance to develop. In some senses it is analogous to the early warning systems employed by banking regulators in some jurisdictions, most notably the United States.

The study initially focuses on the small and medium-sized UK banks' balance sheet characteristics in 1991 Q2, the quarter prior to the announcement of BCCI's closure. This news accelerated the rate at which wholesale deposits were withdrawn from the small banks. At this point the most important leading indicators of failure were a high dependence on net interest income, low profitability, low leverage, low short-term assets relative to liabilities and low loan growth. Taken together, these indicators suggest that the banks that failed over the following three years were already weak by the early 1990s (reflecting the recession at the time).

While they may be helpful in identifying subsequent failures, these indicators cannot be used by regulators or central banks to take pre-emptive policy action. The interval between the signal and failure is too short, so by then, it may have been difficult for regulators to do anything more than manage down the scale of the problems. Indicators of future failure with a longer lead-time would be more useful.

Data from the pre-recession period were therefore analysed. The results suggest that rapid loan growth in the late 1980s boom was a good longer-term indicator of failure. A cyclical comparison indicates that the banks that subsequently failed tended to exhibit a pronounced boom and bust cycle in lending growth, unlike those banks that survived.

1 Introduction

Bank failure has fortunately been a rare event in the United Kingdom. Even more infrequent has been the simultaneous failure of a number of banks that potentially threatens the stability of the financial system. This study uses as a backdrop the period, known as the small banks' crisis of the early 1990s, when failure was last widespread and the system faced a potentially systemic threat. It was the most recent time that the Bank of England provided emergency liquidity support.(1)

This study examines the balance sheet characteristics of the small and medium-sized UK banks in the quarter prior to the announcement of the closure of Bank of Credit and Commerce International SA (BCCI), to see whether the banks that would go on to fail had any distinctive features compared with those that would survive this crisis period. Its goal is to identify leading indicators of failure. This may assist the Bank of England and the Financial Services Authority (FSA) in crisis prevention policy prescriptions before a future crisis has a chance to develop. Without pre-empting the results, some of the characteristics that are found to be important suggest that the banks were already in some distress at the time of BCCI's closure — probably reflecting the ensuing economic recession. So the exercise is repeated using data from earlier in, and prior to, the beginning of the recession.

Although this study focuses on a particular crisis period, it has close parallels with the early warning systems used by banking supervisors to predict either bank failure or weakness (typically defined as regulatory rating downgrade). Reidhill and O'Keefe (1997) give an overview of the development of such systems since the mid-1970s by the three federal banking regulators in the United States (see also Cole, Cornyn and Gunther (1995), Espahbodi (1991), Korobow, Stuhr and Martin (1977), Martin (1977), Korobow and Stuhr (1975), Sinkey (1975), and Meyer and Pifer (1970)). Van den Bergh and Sahajwala (2000) show that the Banque de France and the Banca d'Italia also employ early warning systems. Logan (2000a) summarises a recent seminar on the latest developments in the construction and performance of early warning systems among member institutions of the Basel Committee on Banking Supervision (BCBS).

Other studies have attempted to explain either why banks fail (see Avery and Hanweck (1984)) or the regulator's closure decision (see Gajewski (1989) and Thompson (1992)). The methods and variables used in these are very similar to those employed in early warning systems, the main difference being that early warning systems are constrained to use only lagged independent variables by their need to generate a timely warning for regulators. More recently, attention has focused on modelling the timing of bank failure (see, for example, Cole and Gunther (1995) and Whalen (1991)).

With few exceptions — for example, González-Hermosillo, Pazarbasioglu and Billings (1997) and Laviola, Reedtz and Trapanese (1999), which look at Mexico and Italy respectively — the

(1) See Jackson (1996) for a description of the causes of bank failures in the United Kingdom in recent decades. See Bank of England (1993), George (1994) and Hoggarth and Soussa (2001) for a description of the crisis and its management. For a recent extensive survey on lender of last resort, see Freixas, Giannini, Hoggarth and Soussa (2000).

literature is dominated by studies of banks in the United States. This reflects, at least in part, the relatively small number of banks and the infrequency with which failures occur in some other countries, which undermines the validity of the statistical techniques used. The current study is novel in that it focuses on the United Kingdom. To the extent that the regulatory and business environment in the United Kingdom differs from those in the United States, Italy and Mexico, it should offer new information.

The paper is organised along the following lines. Section 2 describes the UK small banks' sector in the early 1990s and provides an overview of the evolution of the crisis. Section 3 provides an overview of the statistical analysis: the definition of failure used, the data sources employed and the types of variable that were tested to assess their leading indicator properties and reports some descriptive statistics. Section 4 details the results based on data in 1991 Q2 (this being the last quarter before the closure of BCCI on 5 July 1991, an event which escalated the difficulties at several small banks). The last section repeats the analysis using variables measured before the start of the early 1990s recession.

2 The small bank sector in 1991

The UK banking system can be split into three broad groups: the UK retail and merchant banks; the small and medium-sized UK institutions; and UK branches and subsidiaries of foreign banks.[2] Table A shows the number of banks in each category from end-February 1990 up to end-February 1994.[3] This study focuses on the small and medium-sized banks because it is in this sector that bank failures were concentrated in the early 1990s. Moreover, analysis of branches and subsidiaries of foreign banks is complicated by events happening to the parent bank abroad (the period of interest coincides with banking crises in, *inter alia*, Scandinavia, Indonesia, Brazil, Mexico, Venezuela and Japan).

Table A: Authorised banks in the United Kingdom (at end-February)

	1990	1991	1992	1993	1994
UK commercial and merchant banks	75	70	72	73	71
of which, members of the MBBG[(a)]	*n.a.*	*n.a.*	*38*	*37*	*34*
UK branches and subsidiaries of foreign banks	340	336	328	332	360
Small and medium-sized banks	125	116	111	96	80
Total	540	522	511	501	511

n.a. = not available.
(a) See footnote 4 for details on membership of the Major British Banking Groups (MBBG). Figures for 1990 and 1991 are not available because the MBBG classification did not come into existence until April 1991.

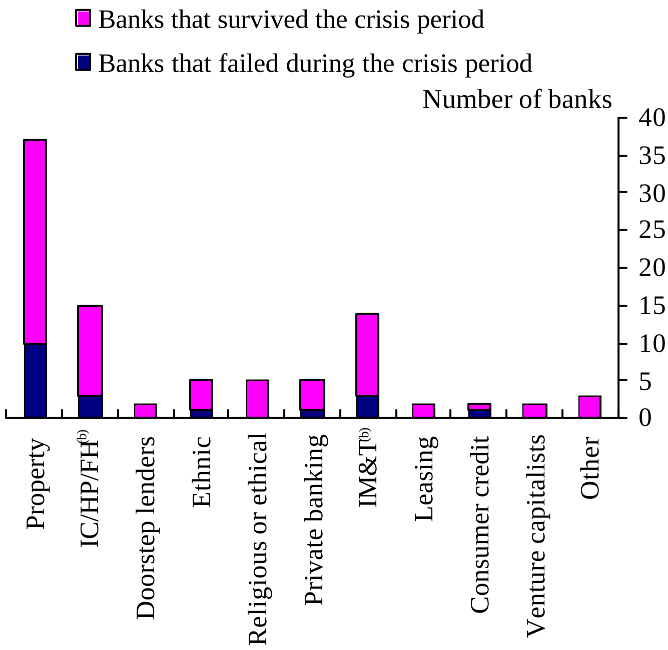
At the end of February 1991, 116 small and medium-sized UK-incorporated banks were authorised. Three of these banks exited the sector before the announcement of BCCI's failure. There is therefore a potential sample of 113 banks. It has been possible to construct a full data set for 95 of them. For reasons explained in Section 3.1 below, three banks have been excluded from

[(2)] The small and medium-sized banks group includes all UK-incorporated banks that were not large commercial or merchant banks. The banks within this catch-all category were labelled small and medium-sized because of the small scale of their balance sheets relative to the two other sectors.
[(3)] Data are taken from the Banking Act Reports of the period.

this investigation because their authorisations were revoked for reasons that potentially cannot be predicted from balance sheet data. The remaining 92 form the sample for the statistical analysis.

Chart 1 splits the small and medium-sized banks operating in 1991 Q2 into peer groups according to their main activity. The largest cohort was the (residential and non-residential) property lenders, which comprised 37 out of the 92 banks. The next two most significant cohorts were the instalment credit/HP lenders/finance houses and investment management/treasury groups, which each included 15 banks. The remainder of the sector undertook a diverse range of activities.

Chart 1
Banks classified by peer group in 1991 Q2[(a)]



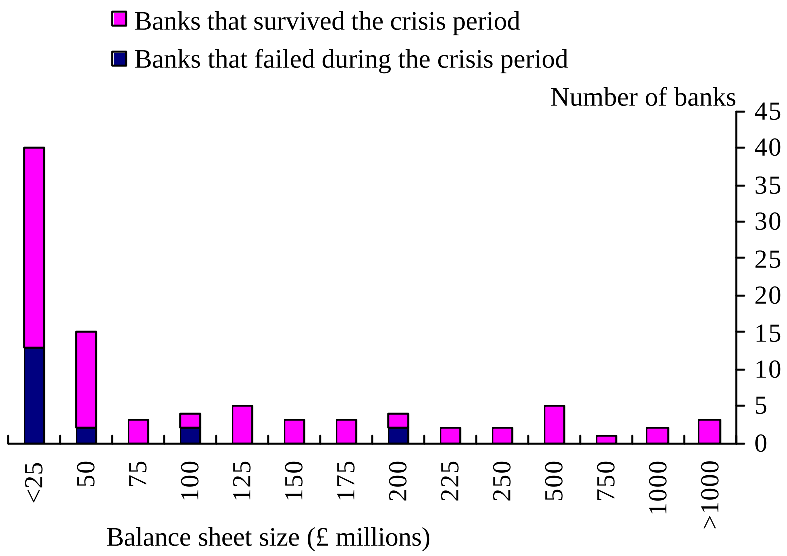
Note: The crisis period is defined as 1 July 1991 to 30 June 1994.

(a) See Section 3.1 for the definition of failure used during the crisis period.
(b) Where IC/HP/FH = Instalment credit/hire purchase/finance houses and IM&T = Investment management and treasury.

An alternative way of looking at the sample of banks is by ownership structure. Just over two thirds of the 92 banks were independent, with no dominant shareholder. A large corporate had a significant stake in, or owned-outright the remainder.

Chart 2 shows a histogram of the 92 banks' balance sheet size in 1991 Q2. The same information is summarised in the 'SIZE' row of Table B. The smallest bank in the sample had total assets of £1.0 million and the largest of £3.2 billion. The mean and median were £166.4 million and £38.2 million, respectively. To put these figures into perspective, Barclays plc, the largest UK bank at that time, had a balance sheet of £138.1 billion at 31 December 1991 while the mean size of the banks in the Major British Banking Groups (MBBG) was £11.8 billion.[4] Both figures dwarf the average size of the individual banks in the small and medium-sized sector. In fact, the *total* assets of the small and medium-sized banks' sector account for only 11% of Barclays' assets and 3.2% of those of the MBBG sector as a whole.

Chart 2
Size distribution of small UK banks in 1991 Q2 [(a)]



Note: The crisis period is defined as 1 July 1991 to 30 June 1994.

(a) See Section 3.1 for the definition of failure during the crisis period.

In the early 1990s, the small and medium-sized UK banks faced pressure on both sides of their balance sheet. On the assets side, the recession adversely affected their customers' ability to service their debts. This was particularly true of customers in the personal and small business sector. The impact of the recession was particularly severe on the property market, which had traditionally been the recipient for much of these banks' lending and also served as security for it.

On the liabilities side, most of the small banks were dependent on wholesale funding to some degree. The deterioration in the quality of their assets, the failure of British & Commonwealth Merchant Bank plc in the summer of 1990 and four small banks in late 1990/early 1991 and, for some foreign institutional depositors difficulties at home, contributed to a gradual withdrawal of this type of funding.[5] On 5 July 1991 the UK banking system was hit by an adverse exogenous shock — the announcement that the Bank of England and banking supervisory authorities in a

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[4] Data on the size of Barclays plc's and Major British Banking Groups' balance sheets are from British Bankers' Association (1992). In 1991 Q2, the MBBG comprised nine banking groups: The Abbey National Group; The Bank of Scotland Group; The Barclays Group; The Lloyds Group; The Midland Group; The National Westminster Group; The Royal Bank of Scotland Group; The Standard Chartered Group; and The TSB Group.
[5] Authority Bank became subject to an administration order on 11 December 1990, Chancery plc on 18 February 1991 and Edington plc on 26 April 1991. Wallace, Smith Trust entered liquidation on 12 June 1991. For further information on the timing of failures, see Deposit Protection Board (1991) and subsequent years' annual reports. For more information on Chancery plc, see Department of Trade and Industry (1998).

number of other jurisdictions were closing down BCCI due to fraud.(6) This news resulted in a rapid increase in the rate of wholesale deposit withdrawals from smaller UK banks. Over the next three years, a quarter of the smaller UK banks would in some sense fail.

3 Variables and data

3.1 Definition of failure

Since the work by Beaver (1966) and Altman (1968), many studies have tried to use balance sheet and other information to predict corporate distress.(7) Most define failure as occurring when a firm's liabilities exceed its assets. This definition is not immediately transferable to the banking industry because bank regulators (at least in the United Kingdom) have the power to close a bank even if it still has positive net worth.(8)(9) Conversely, systemic concerns could motivate the authorities to keep a bank afloat (at least in the short term) that is technically insolvent.

Researchers undertaking studies that attempt to predict the demise of a bank require an alternative definition of what constitutes failure. Most tend to adopt one that reflects the regulators' past judgments and actions. It is therefore a function of the bank regulators' powers, its crisis resolution techniques and its incentives.(10) These obviously change over time (reflecting, for example, legislative changes and fragility of the financial system) and vary across countries.

In this study, a bank is classified as having failed if it underwent any of the following events between 1 July 1991 and 30 June 1994:

I. it entered administration;
II. it entered liquidation;
III. it received liquidity support from the Bank of England;
IV. it had its authorisation revoked by the Bank of England for reasons that could potentially be predicted by the balance sheet and other information used in this study;(11)
V. it voluntarily surrendered its authorisation, except when motivated by corporate restructuring (typically following takeover) or by a strategic review of the benefits of a banking licence (because the entity no longer needed to receive deposits to conduct its consumer credit or lending activity).

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(6) See House of Commons (1992) for information on the supervision and failure of BCCI.
(7) See Benito and Vlieghe (2000) for a brief overview of this literature.
(8) The circumstances under which the Bank of England could revoke a bank's authorisation are set out in Section 11 of the Banking Act 1987. See HMSO (1987).
(9) See Demirgüc-Kunt (1989) for a discussion of the issues surrounding the definition of failure in studies of US bank failure.
(10) Kane (1989) develops a model of bank regulators' decision-making featuring their career incentives and economic, political and bureaucratic constraints.
(11) Some of the Schedule 3 (for example, directors to be fit and proper persons, the business to be directed by at least two individuals, composition of the board, etc) and other criteria under which the Bank could revoke a bank's authorisation were not deemed potentially predictable from the balance sheet data and other indicators used in this study. So three banks that had their authorisation removed for such reasons were dropped from the sample.

The three-year period was chosen because it is when the Bank maintained its heightened scrutiny of the sector; but there is of course some arbitrariness about any particular cut-off point.

3.2 Data sources

The balance sheet and other characteristics that were investigated as potential leading indicators of failure were drawn largely from the banks' regular (confidential) statistical returns to the Bank of England. The scope of the returns increased with the size of the bank and the number of activities it undertook. Data are available on small banks for most key items — the liquidity position, balance sheet, P&L, off balance sheet items, large depositors and large exposures. The major gaps are information on the sectoral pattern of their lending (including exposures to the property sector) and the interest rates on their liabilities and assets.

These data have been supplemented by non-statistical information available to the bank regulators and by some of their qualitative assessments. These included the peer groups in which banks were categorised, a judgment over whether or not a bank had a strong parent, and the regulatory capital target ratio the regulators set for each bank.[12]

In recent years considerable research has been undertaken on market participants' ability to judge the soundness of banks. Flannery (1998) argues that data on the financial market's assessment of a bank's condition should be formally integrated into the monitoring and early warning systems used by bank regulators. Unfortunately, it is not possible to test whether some of the more frequently used market indicators would have had predictive power in the small banks' crisis. These banks' equity and debt tended not to be publicly traded. Only one of the 92 banks in the study had a credit rating at the time, so nor is it possible to use ratings as a proxy for the market's assessment.

3.3 Explanatory variables

The definitions of all the variables considered as potential leading indicators of bank failure are given in Appendix 1. They were selected on the basis that they appeared important in previous similar empirical studies or reflected the prior beliefs of those working on this exercise within the Bank. The characteristics can be categorised into two types. The first aim to measure the potential for a bank to make losses; the second seek to capture the bank's ability to withstand adverse shocks.

(12) The target ratio is set to provide a cushion above the minimum capital requirement ('the trigger ratio') that each bank is required to observe. It is set at a level that the bank regulators judge sufficient to prevent an accidental breach of the trigger ratio. If a bank's capital ratio falls below its target, the regulators would open discussions with the institution's management to ensure that the trigger ratio is not breached. In contrast to many other countries, the capital ratios set by the regulators (these trigger and target ratios) are bank-specific, and are set above the across-the-board 8% Basel minimum.

The variables measuring the potential for losses can in turn be split according to the type of risks: credit, liquidity, concentration and miscellaneous risk.[(13)] Credit risk is proxied in three ways. Rapid loan or total balance sheet growth (LG91 and TA91 respectively) may suggest that a bank is taking on less creditworthy customers.[(14)] A high level of provisions as a share of total assets (POA) may suggest that the bank has been a poor judge of credit risk in the past and this may continue in the future. A high ratio of risk-weighted assets to unweighted assets (RWTTA) indicates that the bank has a high proportion of risky assets as categorised by the 1988 Basel Accord.[(15)] All three measures of credit risk would be expected to be positively correlated with failure.

Three variables are proxies for the risk of making losses due to illiquidity. On the assets side, the ratio of (non-marketable) private sector loans to total assets (LOA) should be relevant to a bank's ability, or inability, to realise cash at negligible cost. On the liabilities side, the share of total deposits made up by deposits from other banks (BAD) may indicate the vulnerability of a bank to a wholesale deposit run. Both of these variables should be positively correlated with failure. Liquidity mismatch (STED) is captured by the difference between short-term (up to eight days) assets and liabilities. It should be negatively correlated with failure.

Four proxies were considered to measure risk due to balance sheet concentration. Two are on the assets side of the balance sheet. A high dependence on claims on relatively few individuals or associated customers (LE) increases risk. Likewise, being classified by the bank regulators within the property sector peer group (PROP) was thought to heighten risk. The dependence on one source of income — net interest income (NII) — could also increase the likelihood of losses because it indicates lack of functional diversification. On the liabilities side, a heavy reliance on a few large depositors (DEPC) might increase the likelihood of liquidity problems.

Three further miscellaneous variables were employed. First, the length of time a bank has been authorised (AGE) may be a proxy for the experience of the bank's management. Second, bank size (SIZE) may reflect the opportunities for diversification (either by type of business or geographical location of their customers), the sophistication of management or their peripheral position in the market place. Finally, the regulators' judgment of a bank's riskiness is proxied by the target capital ratio they set (TAR).[(16)]

A number of variables were experimented with to capture a bank's ability to withstand unanticipated losses (regardless of the type of risk exposure from which they originate). A bank's first line of defence is traditionally regarded as current earnings. These are proxied by two variables — revenue as a percentage of costs (ITCR) and profits as a percentage of total

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(13) The Bank's statistical return on market risk was not introduced until the beginning of 1996, so no proxies for this type of risk are included due to lack of data. As the small and medium-sized banks were not for the most part heavily involved in trading, this seems unlikely to be a substantial loss.
(14) All the variables measuring the change in a particular indicator (rather than its level) are calculated over a one-year time horizon, in order to help isolate the particular point in the cycle in which the variable's behaviour is important. A longer time interval may mask whether the signal occurs in the boom or the recession.
(15) See Basel Committee on Banking Supervision (1988). Since the risk weights under the current Basel Accord are very broad, the ratio of risk-weighted to unweighted assets should be regarded as only a rough guide to credit risk.
(16) For confidentiality reasons, Table B excludes the target ratios that the banking regulators set the banks at the time.

assets (PROF and PROFPR). The capital cushion is the second line of defence. This is measured in two ways: the excess capital ratio over the regulator's target ratio set by the supervisors (XRAR and XRARP) and a leverage ratio — unweighted assets divided by capital (LEV) — which supervisors in the United States use as a backstop to the Basel risk-weighting framework. A possible third line of defence, the presence of a large parent that may bail out a troubled bank, is also included as a dummy variable (PAR).

3.4 Descriptive statistics

Table B reports descriptive statistics for the explanatory variables in the quarter prior to the announcement of BCCI's closure (1991 Q2). Information is presented on the median (column 1), mean (column 5), standard deviation (column 6) and range for the entire sample (columns 7 and 8). The medians for the group of 73 banks that remained in business and the 19 that failed are reported separately (in columns 2 and 3).

Column 4 reports a non-parametric test statistic that evaluates the null hypothesis that the two groups' medians are equal against the alternative that they differ. Details of the test and the intuition behind it are described in Appendix 2. A positive number indicates that the proportion of survivor banks above the two groups' common median is greater than the proportion for the group of failed banks. A negative number suggests the opposite is true. Rejection of the null hypothesis of equal medians in a two-tailed test at three confidence levels (90%, 95% and 99%) is indicated with *, ** and *** respectively.

As is evident from Table B, it is possible to reject the assumption of equal medians for seven of the variables — virtually all are indicators that show that the failed banks' condition had already begun to deteriorate relative to those that remained in business (probably reflecting the impact of the recession). The banks that went on to fail had made more provisions as a proportion of total assets (POA): their median level was 4.6% against 1.4% for the survivors. Their median profit as a percentage of total assets (PROF) was 0% compared with 0.7% for the survivors. The failed banks' capital — the numerator of the risk assets ratio — fell in the year to 1991 Q2 (CAP), while for the survivors it rose (-1.1% against 7.7%).

It is also possible to reject the null hypothesis of a common median for the two groups' loan growth in the year to 1991 Q2 (LG91) and, similarly, of a common media for the rate of change of loan and asset growth between 1990 Q2 and 1991 Q2 (LG91/90 and TA91/90). These data indicate that balance sheet growth was both *lower* and *fell* more rapidly for the failures than for the survivors.

4 Regressions and results

4.1 Regressions

The dependent variable is constructed as a binary variable. It takes the value 1 if the bank is defined as a failure, as specified in Section 3.1. It takes the value 0 if it continued to trade for the whole period.

Table B: Descriptive statistics of variables in 1991 Q2

Variable	Median	Median	Median	Test statistic[a]	Mean	SD	Min	Max
	All	Survivors	Failures		All	All	All	All
Column	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
AGE[b]	11.0	11.0	11.0	n.a.	9.8	2.1	4.0	11.0
BAD	4.7	1.4	11.1	-0.26	22.0	29.2	0.0	99.1
CAP	5.4	7.7	-1.1	2.83***	5.5	26.5	-79.8	123.5
DEPC	50.8	51.4	49.5	0.26	51.1	28.4	0.0	100.0
ITCR	186.4	184.4	210.6	-0.26	289.2	386.6	69.6	3144.3
LE[c]	31.9	28.6	47.9	-1.65	36.6	25.0	0.0	97.7
LEV	425.2	443.8	367.4	1.29	587.8	668.6	24.1	3508.7
LEVD	0.2	-0.1	1.7	-0.47	-30.3	237.9	-1631.9	540.8
LG91	7.1	10.8	2.1	1.80*	13.4	49.2	-52.8	402.6
LG91/90	-5.6	0.2	-15.1	3.35***	-9.0	85.5	-623.5	371.8
LOA	94.2	93.2	96.4	-1.29	85.2	18.8	22.0	100.0
NII	83.9	81.3	89.3	-1.29	76.1	24.9	6.0	100.0
POA	1.7	1.4	4.6	-2.32**	4.1	7.8	0.0	52.2
PROF	0.6	0.7	0.0	2.32**	0.1	4.9	-37.5	7.7
PROFPR	3.6	3.6	4.4	-0.26	4.1	3.5	-4.5	17.7
RWTTA	71.8	71.5	76.6	-0.77	73.2	50.2	19.4	468.7
SIZE[d]	38.2	44.0	17.3	2.32**	166.4	435.0	1.0	3165.5
STED	1.0	1.0	1.9	-0.26	2.4	31.0	-86.8	96.2
TA91	6.5	9.8	-2.2	1.29	11.5	37.1	-41.2	252.2
TA91/90	-5.5	-3.2	-13.2	1.80*	-9.4	58.2	-315.3	215.3
XRAR	10.6	11.2	8.7	0.77	22.7	34.4	-4.7	170.6
XRARD	-0.1	0.0	-0.3	0.26	1.4	9.7	-22.0	46.6
XRARP	63.3	69.4	47.4	0.77	135.1	206.8	-27.8	985.4

[a] Where *,** and *** in Table B indicate significance using the t-distribution at the 90%, 95% and 99% confidence interval.
[b] This test is inoperable on the variable AGE because it is bounded by the date of the Banking Act 1979 and the median lies at the upper bound.
[c] Constructed using just the 67 banks for which this information is available.
[d] In £ millions, rather than the natural logarithm used in the regressions.

Unfortunately, one of the statistical forms used to construct many of the independent variables that are to be tested for their leading indicator properties was only introduced in 1989. The timing reflects the Bank's implementation of the 1988 Basel Accord. This means that it is only possible to construct most of the variables for the two years prior to the start of the crisis period. It was therefore decided to undertake a cross-sectional study, using data constructed in 1991 Q2. At the risk of pre-judging the results that follow, most of the variables that are helpful in predicting failure showed that the banks that went on to fail were already weak by then. To test whether there are any useful longer leading indicators of failure, the analysis was repeated using variables constructed for 1990 Q2, to which were added the few available variables (illiquidity mismatch, the share of assets that can easily be turned into cash, loan/asset growth, size and the share of total deposits from banks) constructed at the second quarter of each year back to 1988 (the height of the boom).

The two cross-sectional regressions were estimated using logit and probit estimation techniques. In practice, the choice of estimation technique made little difference to the results. Logit was used as interpretation of the results is more straightforward. Cox and Snell (1989), Cramer (1991), Greene (1993) and Maddala (1983) all provide excellent expositions of this technique.(17)

In this type of study, model validation is usually undertaken by out-of-sample forecasts. The option of combining the estimated coefficients with data collected at a subsequent point to see how accurately the model classifies banks over a later time period was not felt worthwhile as there were too few failures in the subsequent years for it to be a useful test. Instead, the estimation was undertaken on 84 out of the 92 banks available. Eight banks were 'held back' to evaluate model performance. In direct proportion to the sample as a whole, these included six banks that continued in business and two that failed. The selection of the six and two banks respectively, within the survivor and failure groups, was random.

4.2 Variable selection

The explanatory variables for use in the estimation are described in Appendix 1 (and briefly in Section 3.3). There are four measures of a bank's exposure or vulnerability to credit risk (LG91, TA91, POA, RWTTA), three measures of balance sheet liquidity (BAD, LOA and STED), three of current earnings (ITCR, PROF and PROFPR), and two of capital adequacy (XRAR (XRARP) and LEV).(18) As inclusion of any more than one measure of each type of risk or the bank's ability to withstand unanticipated losses could potentially introduce multicollinearity into the equation, it was decided to select between them and enter the preferred measure of each into the general specification of the regression.(19)

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(17) Both logit and probit models are estimated using maximum likelihood. For consistency this technique requires large sample sizes. A sample of 92 observations is admittedly on the small side, but many other empirical studies have used the same technique on similarly sized samples.
(18) As there was thought to be no overlap in what the variables reflecting balance sheet concentration and miscellaneous risks were designed to measure, these (with the exception of the target ratio) are all included in the regression simultaneously. It was decided to include one measure of each type of ability to resist losses.
(19) The target ratio (TAR) that the bank regulators set the banks was dropped from the regressions because it was thought that it should be related to all the variables that were proxying risk.

The choice of which measure of risk type or capacity to withstand shocks to adopt was based on the Akaike information criterion. Holding all other variables constant, each measure of, for example, credit risk was entered in the regression in turn to see which maximised the value of this model selection criterion. As there are multiple measures of the variables being held constant and it was felt necessary to see the interaction between all definitions, this procedure was repeated using these as well. Where differences in equation specification yielded different results, the final selection of the appropriate definition of a variable was made on the basis of which had the least overlap with the other variables (lowering the likelihood of multicollinearity) and most boosted the accuracy of the within-sample predictions of the failed banks.(20)

Loan growth in the year to 1991 Q2 (LG91) was selected in preference to the other measures of credit risk for inclusion in the empirical analysis. This was because it outperformed all the other measures in the scale of its impact on the AIC. The sight to eight day mismatch (STED) was the dominant measure of liquidity. The post-tax (and provisions) return on total assets (PROF) outperformed the other earnings variables. The leverage ratio (LEV) was the dominant measure of capital.

4.3 Results using data for 1991 Q2

The general specification of the regression focusing on the quarter prior to the shock of the announcement of BCCI’s closure is shown in Regression 1 in Table C. Regression 2 shows the parsimonious form tested down by excluding sequentially the most statistically insignificant variable with the objective of maximising the value of the AIC. The discussion in this section focuses on this preferred regression.

Using the estimated coefficients shown in Regression 2 it is possible to calculate the marginal impact on the probability of failure of a unit change in the value of each of the continuous explanatory variables (evaluated at their mean). For ease of comparison these figures have been manipulated to show what scale of movement would be necessary in each of the variables to increase the likelihood of failure by 1% in this crisis. The results are shown in Table D. The medians of the group of failed and survivor banks are inserted to the right-hand side of this figure to give a sense of scale. These calculations are used to explain the results.

In terms of statistical significance, the most important leading indicator in Regression 2 is loan growth in the year to 1991 Q1 (LG91). The sign on the coefficient is negative suggesting that at the time of BCCI’s closure banks with lower annual loan growth were more likely to fail. This may reflect supply-side factors: the weakened banks were having to write off past loans, their funding (deposits) was growing less rapidly, or they needed to reallocate their staff resources away from sales and marketing towards nursing existing customers. It is unlikely to be explained by a capital constraint: as evident from Table B their median risk assets ratio is 8.7 percentage points above the supervisors’ target ratio (XRAR). There is also no evidence of their substituting

(20) West (1985) uses factor analysis to decide the preferred measure of each risk or ability to withstand unanticipated losses.

Table C: Regression results based on 1991 Q2 data [(a)(b)]

	Regression 1	Regression 2
Constant (CON)	-7.5165	-7.0476
	(-1.5816)	*(-2.0455)***
Length of authorisation (AGE)	0.2248	0.2379
	(1.0277)	*(1.0953)*
Deposit concentration (DEPC)	-0.0105	
	(-0.7244)	
Loan growth in the year to 1991 Q2 (LG91)	-0.0635	-0.0606
	*(-2.9811)***	*(-3.0259)****
Balance sheet (SIZE)	0.0465	
	(0.1618)	
Dependence on net interest income (NII)	0.0708	0.0644
	*(2.1817)***	*(2.2390)***
Membership of property peer group (PROP)	0.6236	
	(0.8055)	
Liquidity mismatch (STED)	-0.0353	-0.0303
	*(-2.2373)***	*(-2.1100)***
Leverage ratio (LEV)	-0.0034	-0.0030
	*(-2.2525)***	*(-2.3554)***
Large parent (PAR)	-1.5474	-1.4738
	(-1.4663)	*(-1.6690)*
Profits as a percentage of total assets (PROF)	-0.4015	-0.3868
	*(-2.4883)****	*(-2.5003)****
Log-likelihood	-25.7309	-26.3500
Akaike information criteria	-36.7309	-34.3500
Schwarz Bayesian criterion	-50.1004	-44.0733
Pseudo R^2	0.3918	0.3772

(a) T-statistics appear in italics in parenthesis below the coefficient.

(b) Where *, ** and *** indicate statistical significance at the 90%, 95% and 99% confidence interval, respectively.

away from high risk weighted assets into lower ones. In fact, the converse is true with unweighted assets falling by more (2.2%) in the year to 1991 Q2 than weighted assets (1.0%). Low loan growth may also reflect demand-side factors. Borrowers from the banks that go on to fail may have been hurt more by the recession than the customers of survivor banks. This, in turn, may have reflected inadequate screening of potential borrowers in the past. The estimated coefficient suggests that, *ceterius paribus*, the likelihood of failure in this crisis is 1% higher for every 3.2 percentage point decline in annual loan growth.

Table D: What would increase the likelihood of failure by 1% in the small banks' crisis of the early 1990s and the medians of the failed and survivor banks

		Median of the two groups	
Indicator	Movement	Failed	Survivor
Loan growth in the year to 1991 Q1 (LG91)	-3.2	2.1	10.8
Dependence on net interest income (NII)	3.0	89.3	81.3
Liquidity mismatch (STED)	-6.5	1.9	1.0
Leverage ratio (LEV)	-66.1	367.4	443.8
Profits as a percentage of total assets (PROF)	-0.5	0.0	0.7

Bank failure is also found to be positively related to dependence on net interest income (NII). This may reflect the reduction in risk gained from undertaking activities that earn uncorrelated income streams. In addition, the earnings stream from traditional lending activity may have been more volatile than other types of income.[21] Either way, hindsight suggests that a management strategy of diversifying into different types of business to earn fees, commission or trading income may have been more prudent. In quantitative terms, Regression 2 suggests the likelihood of failure in this episode would have been increased by 1% if the share of income earned from net interest was raised by 3 percentage points.

The other measure of risk found to be statistically significant is the liquidity mismatch between short-term assets and liabilities (STED). As expected, the coefficient suggests that the more short-term liabilities exceed short-term assets the greater the likelihood of failure. In quantitative terms, however, a large increase in the share of short-term net assets as a proportion of total assets (6.5 percentage points) is required to lower the probability of failure by 1% in this crisis.

The other four variables that attempt to capture risks — length of authorisation (AGE), deposit concentration (DEPC), size (SIZE) and the exposure to property dummy (PROP) — were all found to be statistically insignificant.[22] Given the importance attached to property lending by the bank supervisors at the time, the insignificance of this variable is somewhat surprising. It may reflect problems over the variable's construction: if it was possible, greater differentiation

[21] See Denney, Staikouras and Wood (2000) for an investigation into the financial stability implications of banks' increasing reliance on non-interest income.
[22] It has not been possible to collect data on the large exposures of all the banks in the sample. However, regressions on the sub-sample of banks for which exposures are available suggest it is statistically significant and correctly signed (ie an increase in the concentration of lending increases the probability of failure). These results are not shown.

on the extent of banks' exposures to the property sector or the distinction between whether the exposures were to residential or commercial property may have been helpful.(23)(24)

Two of the three variables that attempt to measure a bank's overall ability to resist shocks are statistically significant. The other is borderline. The sign of the coefficient on the profitability variable (PROF) is in line with expectations: lower profitability is associated with failure. In quantitative terms, Regression 2 suggests the likelihood of failure in this crisis is 1% lower for every 0.5 percentage point increase in the profits-to-assets ratio.

At first sight the coefficient on the leverage ratio (LEV) is counterintuitive and contradicts the findings in the majority of other studies (see, for example, Estrella, Park and Peristiani (2000) for evidence on US banks). It is negatively signed, suggesting that *lower* rather than higher leverage is associated with failure. The explanation does not appear to lie in the bank regulators forcing the weakened banks to hold high capital in relation to assets — the inverse of leverage. There was little difference in the actual risk-asset ratios of the failed and survivor banks. To the extent that the private sector had sufficient information to monitor the small and medium-sized banks' leverage ratios, it might reflect market discipline. If the banks which subsequently failed were already perceived by the market as being weak, they may have been required to hold high levels of capital before potential counterparties would lend to them. Alternatively, an insufficient number of counterparties may have been willing to deal with them (or in the desired volume), making them unable to expand their balance sheet and raise their leverage.

Other researchers, for example Thompson (1991), have also found capital variables to be statistically significant, but counter-intuitively signed in predicting bank failure over a short (although not longer) time horizons. They have attempted to justify the result in two ways. First, it may reflect attempts by banks beginning to experience difficulties to improve cosmetically their capital position by selling assets on which they have capital gains and deferring the sale of assets on which they have capital losses. Second, it may reflect strong banks being more aggressive in recognising and making provisions and writing off problem loans than their weaker counterparts; or, conversely, weak banks being slow in doing so, so that assets are effectively overvalued in accounts and capital adequacy flattered by capital ratios.(25) Both these explanations, and also the market discipline one discussed above, rely on the premise that the banks which went on to fail were already fundamentally weak.

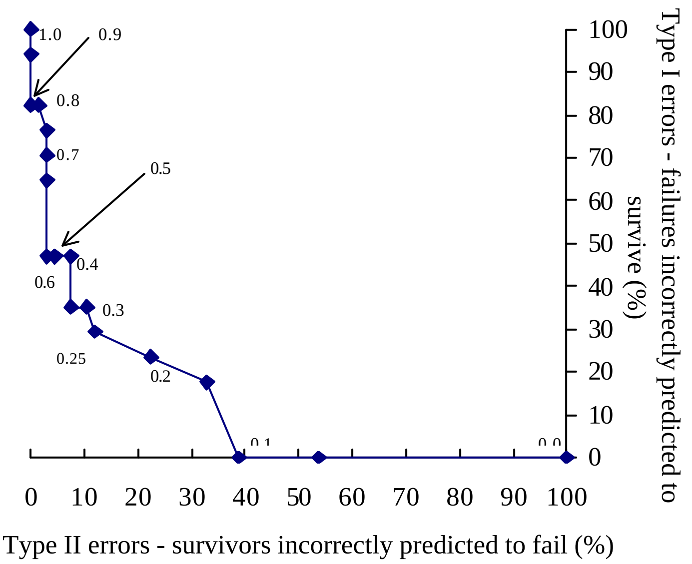
The large parent dummy borders on statistical significance at the 90% confidence interval. The sign of the coefficient is as expected, suggesting that small and medium-sized banks were more likely to fail if they were not owned by large corporates. Those that had large parents may have benefited from actual parental support or, at least, avoided depositor withdrawals because of an

(23) Between peak and trough, commercial property prices fell by 27% (1989 Q4 to 1993 Q2), while residential property prices fell by 14% (1989 Q3 to 1992 Q4).
(24) In the early 1990s, banks with total assets of less than £100 million were not required to complete the statistical return on the industrial composition of their exposures to UK residents. This return included information on exposures to the property sector. At the time, bank regulators would have been able to request management accounts information, which filled the gap. Such information is not readily available to the author.
(25) See Jackson and Lodge (2000) for a discussion of the financial stability implications of the banking industry's use of historical cost versus fair value accounting.

expectation of parental support. Other researchers, for example Abrams and Huang (1987) and Belongia and Gilbert (1990), have also found that the presence of a parent — in their case a bank holding company — reduces the likelihood of bank failure.(26)

The performance of Regression 2 in terms of Type I errors (the failure to predict an actual failure) and Type II errors (a false prediction of failure when in fact the bank remains in business) is shown in Chart 3. It is constructed using cut-off points where the probability of failure increases at 5% intervals within the range 0 and 1. It exhibits the normal concave shape illustrating the trade-off between Type I and Type II errors.

Chart 3
Type I & II errors of Regression 2 over various cut-off points



Overall, the model performs well. At a cut-off point of 0.25 it predicts 12 out of the 17 (71%) within-sample failures and 59 of the 67 (88%) banks that survived.(27) This equates to Type I and Type II errors of 29% and 12%, respectively. At this cut-off point it correctly predicts all eight of the out-of-sample failure/survival outcomes, including the two banks that failed.

Table E provides information on the within-sample classification accuracy of studies that attempt to predict the failure of US banks. It can be seen that the current model's Type I and II errors are not out of line with the remainder, especially when comparison is drawn against the studies that forecast over a time frame longer than one year. The current study tries to predict failure over a one month to three year window.

(26) Gajewski (1989) also finds a bank holding company variable statistically significant and negatively signed in his regulatory bank closure model. He argues that it reflects regulatory forbearance: the regulator being reluctant to close a subsidiary of a multi-bank holding company (MBHC) in case it precipitates runs on its other banking subsidiaries.
(27) This cut-off point produced the second lowest sum of the percentage of Type I and Type II errors. It was preferred to the global minima because the latter had a high level of Type II errors. See Bell and Pain (2000) for a discussion of the trade-off policy-makers face in selecting a cut-off point in early warning systems.

While the performance of Regression 2 is encouraging, it is not particularly helpful from a policy perspective. Most of the statistically significant leading indicators of bank failure in the small and medium-sized bank sector in mid-1991 discussed in this section — namely, low loan growth, low profitability, low short-term assets relative to liabilities and, arguably, low leverage — show that by the time of BCCI's closure the banks that went on to fail were already showing signs of fragility. They confirm the results found in the univariate tests. While they may be helpful in identifying subsequent failures, these indicators cannot be used by regulators/central banks to take pre-emptive policy actions to avoid bank or banking system weakness in the first place. In order to find indicators of future failure before banks actually weakened, data from an earlier (pre-recession) period were analysed.

Table E: Within-sample classification accuracy of selected US bank failure prediction models[(a)]

Author	Date of failures	Date of independent variables	Estimation technique	Type I errors (%)	Type II errors (%)
Meyer and Pifer (1970)	1948-1965	1 year before failure[(b)]	Discriminant analysis	10.0	13.0
	1948-1965	2 years before failure[(b)]	Discriminant analysis	23.0	7.0
Martin (1977)	1971-1972	1970	Logit	50.0	15.3
	1975-1976	1974	Logit	8.7	8.9
Espahbodi (1991)	1983	1982	Logit	13.2	11.4
	1983	1981	Logit	21.6	27.3
Thompson (1991)	1985	1984	Logit	11.3	10.5
	1986	1985	Logit	11.3	9.6
	1987	1986	Logit	9.4	7.0
Thompson (1992)	1984-1989	6-12 months before failure[(b)]	OLS & Logit	8.7	6.7
		24-30 months before failure[(b)]	OLS & Logit	17.2	17.8
		42-48 months before failure[(b)]	OLS & Logit	27.2	20.8

(a) Studies selected on the basis that the author reports Type I and Type II errors for the within-sample estimation.
(b) These studies use a pooled sample, where the explanatory variables are constructed at the specified time interval prior to failure, irrespective of the precise timing of the failure.

4.4 Results using data for 1990 Q2 or before

Column 4 of Table F repeats the univariate analysis for the variables constructed at 1990 Q2. This time around it is possible to reject the assumption of equal medians for seven of the variables. Five of them are measures of bank risk (balance sheet expansion (LG90 and TA90),

Table F: Descriptive statistics of variables in 1990 Q2[a]

Variable	Median	Median	Median	Test statistic[b]	Mean	SD	Min	Max
	All	Survivors	Failures		All	All	All	All
Column	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
AGE[c]	10.0	10.0	10.0	n.a.	8.8	2.1	3.0	10.0
BAD	9.6	1.8	16.8	-1.29	22.1	29.5	0.0	99.4
DEPC	46.6	41.8	55.5	-2.32**	48.1	27.2	0.6	100.7
ITCR	197.4	196.3	200.4	-0.26	307.1	457.2	83.6	4083.3
LEV	424.1	456.7	345.1	2.32**	618.2	788.4	5.9	5108.4
LG88	19.1	14.1	28.8	-1.29	24.3	37.1	-78.9	201.4
LG89	19.1	18.3	25.5	-0.77	24.0	34.5	-37.1	200.7
LG90	14.1	11.0	17.0	-1.80*	22.4	65.3	-69.1	570.7
LG89/88	1.4	2.1	-3.7	0.77	-0.2	49.5	-164.6	165.0
LG90/89	-4.5	-4.5	-8.5	0.26	-1.6	73.5	-146.7	590.7
LOA	92.8	92.0	96.8	-1.29	85.1	17.9	20.7	100.0
NII	85.0	84.7	88.5	-0.77	77.2	23.5	-13.2	101.2
POA	0.8	0.7	1.3	-1.29	2.6	6.6	0.0	48.3
PROF	1.1	1.1	1.0	0.77	1.4	3.2	-22.2	13.0
PROFPR	3.6	3.5	4.1	-1.29**	4.4	3.7	-2.4	16.3
RWTTA	71.6	71.7	68.5	0.26	69.7	38.0	6.9	308.4
SIZE[d]	33.9	46.5	15.0	1.80*	151.9	401.1	0.8	2846.1
STED	-1.0	-3.7	2.0	-2.32**	12.5	131.2	-111.0	1176.3
TA88	19.1	17.1	20.8	-0.88	23.9	29.1	-42.2	127.3
TA89	18.9	18.7	24.9	-1.09	24.4	35.8	-75.4	200.9
TA90	14.6	12.7	25.0	-1.86*	17.8	34.8	-60.5	261.0
TA89/88	1.1	1.9	1.0	0.77	0.5	46.3	-161.2	165.7
TA90/89	-4.1	-3.6	-8.5	0.26	-6.6	43.9	-146.6	206.8
XRAR	11.1	10.9	12.2	-0.26	21.3	30.4	-8.7	163.6
XRARP	-30.9	-30.2	-32.1	0.26	24.8	181.7	-143.5	813.5

(a) Or earlier, where indicated by the variable name.
(b) Where *,** and *** in Table F indicate significance using the t-distribution at the 90%, 95% and 99% confidence interval.
(c) The test is inoperable on the variable AGE because it is bounded by the date of the Banking Act 1979 and the median lies at the upper bound.
(d) In £ millions, rather than the natural logarithm used in the regressions.

Table G: Regression results based on data at 1990 Q2 or before [a] [b]

	Regression 3	Regression 4
Constant (CON)	-4.9298	-2.9159
	(-1.2968)	*(-1.0678)*
Length of authorisation (AGE)	0.4027	0.3157
	*(1.7802)**	*(1.5746)*
Deposit concentration (DEPC)	0.0245	0.0194
	(1.6389)	*(1.4665)*
Loan growth in the year to 1988 Q2 (LG88)	0.2883	0.2837
	*(2.7228)****	*(3.0908)****
Balance sheet (SIZE)	-0.3328	-0.3194
	(-1.0808)	*(-1.7037)**
Dependence on net interest income (NII)	0.1223	
	(0.6913)	
Membership of property peer group (PROP)	0.6200	
	(0.9159)	
Liquidity mismatch (STED)	-0.0073	
	(-0.7776)	
Leverage ratio (LEV)	-0.0000	
	(-0.0568)	
Large parent (PAR)	-0.3650	
	(-0.3659)	
Profit as a percentage of total assets (PROF)	-0.0511	
	(-0.3300)	
Log-likelihood	-31.1530	-32.3463
Akaike information criteria	-42.1530	-37.3463
Schwarz Bayesian criterion	-55.5225	-43.4234
Pseudo R^2	0.2637	0.2355

Source: Bank calculations.

(a) T-statistics appear in italics in parenthesis below the coefficient.

(b) Where *, ** and *** indicate statistical significance at the 90%, 95% and 99% confidence interval, respectively.

size (SIZE), liquidity (STED) and deposit concentration (DEPC)). In four out of five cases (the exception being liquidity), the subsequent failures group median appears more risky than the survivor group median.

Regressions 3 and 4 in Table G show the general and parsimonious forms respectively of the model estimated on data constructed at 1990 Q2 or earlier for the few variables for which data were available. The most statistically significant variable from the earlier period regression is loan growth in the year to 1988 Q2 — the peak of both the GDP and lending growth cycles in the previous boom. Unlike the analogous variable in the 1991 Q2 regressions, its coefficient is positively signed, suggesting that banks which failed in the subsequent recession had higher loan growth at the height of the boom than their competitors which survived.(28)

The change in sign of the two coefficients between the two estimation periods may well be linked. A poor selection of credit risks in the boom phase may have caused loan write-offs, or lower customer demand for loans, in the ensuing recession. This explanation is consistent with the life cycle of a bank failure view of Reidhill and O'Keefe (1997) from the Federal Deposit Insurance Corporation (FDIC) in the United States. In the first stage, there is rapid loan growth, concentrations may emerge, underwriting standards may weaken, and it may be financed by more volatile funding sources. In the second stage, loan quality problems begin, profits start to decline and inadequate provision levels emerge. In the final stage, the deterioration in asset quality becomes a serious problem, and loan losses and write-offs reach high levels. The bank makes substantial steps to cut its expenses and assets are sold off. In some cases, these measures may allow the bank to survive; in others it will fail.

Some support for the contention that the change in the sign of the coefficients on the loan growth variables in the two regressions may well be connected comes from loan growth distributions shown in Table H. In 1988 almost 40% of the banks within the highest loan growth quartile went on to fail compared with 17% or less of banks in the lower growth quartiles. However, as economic growth declined, so did the loan growth of the failed banks relative to that of the survivors. By mid-1991 not a single bank within the then highest loan growth quartile went on to fail.

Table H: Share (%) of future bank failures in each loan growth quartile 1988 Q2 – 1991 Q2

	% of banks in each quartile that would fail (between 1991 Q2 - 94 Q2)			
Loan growth by quartile	1988 Q2	1989 Q2	1990 Q2	1991 Q2
Quartile 1 – lowest	17.4	17.4	13.0	26.1
Quartile 2	13.0	17.4	13.0	30.4
Quartile 3	13.0	13.0	43.5	26.1
Quartile 4 – highest	39.1	34.8	13.0	0.0

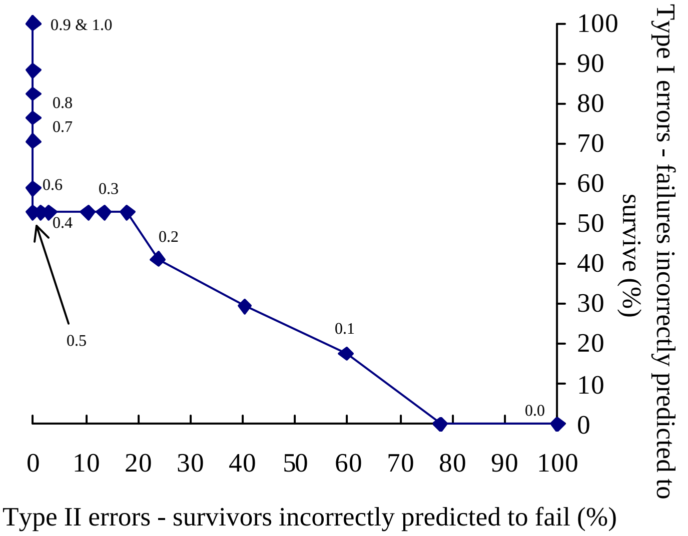
(28) Office of the Comptroller of the Currency (1988) also finds that an overly aggressive or excessively growth-minded strategy relative to circumstances was prevalent amongst national banks that failed in the United States between 1979 and 1987.

Size also seems to be important (at the 90% significance level). Smaller banks within the small and medium-sized bank sector tended to fail more often than larger ones. This is consistent with the more general picture that failures in the post-BCCI period were concentrated in that sector rather than commercial and merchant banks. It may reflect their lower opportunities for diversification (either by business type or by location of their customers), the abilities of management, or their peripheral position in the market. It is puzzling, however, that the size variable was not statistically significant in the later 1991 Q2 regression.

Two other variables — length of authorisation (AGE) and deposit concentration (DEPC) — are almost statistically significant. It is interesting that the sign on the coefficient of AGE is positive, suggesting that the longer a bank had held its banking licence the *more* likely it was to fail. This runs contrary to the original rationale for including the variable — as a proxy for the experience of the management — and suggests that the interactions involved are not well specified. One possible, albeit speculative, explanation may be that the authorisation criteria used by the bank regulators became more rigorous over time.

Chart 4 shows the accuracy of Regression 4 in classifying the banks on which it was estimated as survivors or failures across the spectrum of cut-off points. At the preferred cut-off point of 0.5, Regression 4 correctly predicts half — eight out of the seventeen — of the within-sample failures and all of the survivors.(29) Out of sample, it accurately predicts the outcome for the six banks that survived but does not predict the two that failed.

Chart 4
Type I & II errors of Regression 4 over various cut-off points



At the preferred cut-off points, Regression 4 performs less well than Regression 2. Many other studies have also found that predictive performance deteriorates as the interval between the measurement of the explanatory variables and the failure increases. For example, Table E shows

(29) This cut-off point was selected because it minimises the sum of Type I and Type II errors.

that Espahbodi (1991) and Thompson (1992) find an increase in both Type I and Type II errors as time elapses between data construction and bank failure, while Meyer and Pifer (1970) find that just Type I errors increase.

5 Conclusion

This study attempts to find leading indicators of bank failure based on the experience of the small and medium-sized UK banks in the small banks' crisis of the early 1990s. It should come with a health warning in that it is a study of a particular episode, and the economic environment, the composition of the small banks' sector and the regulatory framework has changed and will continue to change in the future. With that caveat in mind, the most important leading indicators of future failure on the eve of BCCI's closure were found to be a high dependence on net interest income, low profitability, *low* leverage, low short-term assets relative to liabilities and low loan growth. Most of these indicators show that the banks that went on to fail were already weak by mid-1991. Going back further in time, rapid loan growth in the previous boom was found to be a good *longer-term* indicator of failure. Thus, unlike the survivors, banks that subsequently failed exhibited a pronounced boom and bust cycle in lending growth.

Appendix 1: Data description

This appendix details the construction of the variables used in the statistical analysis in this paper. Unless otherwise indicated variables are constructed at 1990 Q2 and 1991 Q2.

AGE **Age**

Number of years the bank had been authorised to accept deposits under the Banking Act 1979.

BAD **Reliance on bank deposits**

The percentage of a bank's deposits placed by other UK banks.

CAP **Change in net capital over the past year**

The percentage change in the level of net capital in the year to 1991 Q2.

DEPC **Deposit concentration**

The size of the ten largest deposits expressed as a percentage of total deposits.

ITCR **Income to cost ratio**

Total income earned over the past year expressed as a percentage of total costs incurred over the past year.

LE **Large exposures**

Ten largest exposures as a percentage of total assets.

LEV **Leverage**

Total liabilities minus total net capital expressed as a percentage of total net capital.

LEVD **Change in leverage in the year to 1991 Q2**

The difference in the level of the leverage ratio between 1991 Q2 and 1990 Q2 (expressed in percentage points).

$LGYear_t$ **Loan growth in the year to Q2 of $Year_t$**

Growth in loans to the private sector in the year to the second quarter of $Year_t$ (expressed as a percentage). Eg LG91 is the growth in loans to the private sector in the year to 1991 Q2.

$LGYear_t/Year_{t-1}$ **Difference in rate of loan growth in the $Year_t$ relative to $Year_{t-1}$**

Growth in loans to the private sector in the year to the second quarter of $Year_t$ minus the growth in the year to the second quarter of $Year_{t-1}$ (expressed in percentage points).

LOA **Loans as a percentage of total assets**

Loans as a proportion of total assets (expressed as a percentage).

NII **Net interest income**

Net interest income earned over the past year expressed as a percentage of total income earned over the past year.

PAR **Owned by a large parent dummy**

A dummy variable which takes the value 1 if the bank was owned by a large parent. Otherwise it takes the value 0.

POA **Provisions as a percentage of total assets**

Specific provisions against bad and doubtful debts and provisions against the value of investments other than trading investments as a percentage of total assets.

PROF **Profitability net of tax and provisions**

Profits (net of tax and provisions) earned over the past year expressed as a percentage of total assets.

PROFPR **Profitability pre tax and provisions**

Profits (pre tax and the subtraction of provisions) earned over the past year expressed as a percentage of total assets.

PROP **Property dummy**

A dummy variable which takes the value 1 if the bank was a member of the banking supervisors' first charge residential mortgage lenders and other property secured lenders peer groups. Otherwise it takes the value 0.

RWTTA **Risk weighted assets expressed as a percentage of total assets**

Risk-weighted assets expressed as a percentage of total assets.

SIZE **Total assets**

The natural logarithm of the sterling value of the bank's total assets.

STED **Sight to eight day liquidity mismatch**

Total assets of less than eight days residual maturity minus total liabilities due over the same time horizon. The net figure is then expressed as a percentage of total assets.

TAR **Target ratio**

The target ratio that the banking supervisors set the bank.

$TAYear_t$ **Total assets growth in the year to Q2 of $Year_t$**

Growth in total assets in the year to the second quarter of $Year_t$ (expressed as a percentage).
Eg TA91 is the growth in total assets in the year to 1991 Q2.

$TAYear_t/Year_{t-1}$ **Difference in rate of total asset growth in the $Year_t$ relative to $Year_{t-1}$**

Growth in total assets in the year to the second quarter of $Year_t$ minus the growth in the year to the second quarter of $Year_{t-1}$ (expressed in percentage points).

XRAR **Excess capital over regulatory capital requirement**

The risk assets ratio minus the target ratio set by the banking supervisors within the Bank at the time (expressed in percentage points).

XRARD **Difference in the level of excess capital between 1991 Q2 and 1990 Q2**

The difference in the level of the excess of capital over the regulatory capital requirement (XRAR) between 1991 Q2 and 1990 Q2 (expressed in percentage points).

XRARP **Excess capital over regulatory capital requirement expressed as a percentage of the latter**

The risk assets ratio minus the target ratio expressed as a percentage of the target ratio.

Appendix 2: Test of common medians for two univariate data sets

The discussion of this test closely follows Cooper and Weekes (1983). The test evaluates the null hypothesis that the median of one data set equals the median of another against the alternative that they differ. No assumption is required that the values from either data set can be modelled by a particular probability distribution or indeed that they follow the same unspecified one. This is because it rests on a property common to all distributions, namely there is a probability of 0.5 that any randomly drawn data value will be below the median.

To undertake the test, the median of the two data sets combined is calculated. If the null is true, namely that the two data sets can be modelled by distributions with the same median, this value should be a good estimate of it. The proportion of values in each data set above the combined median is then calculated. If the null hypothesis is true, the two proportions should be roughly equal to 0.5 and the difference between them should be small. If the two proportions are markedly different it seems likely they can be modelled by two distributions with different medians.

The test statistic is set out in Equation 1. Ps and Pf are the proportions of the survivor and failed banks' values that lie above the combined groups' median respectively. As stated above (Ps-Pf) should be small if the null hypothesis is true.

Equation 1
$$T = \frac{(Ps - Pf)}{\sqrt{(P.(1-P).(1/Ns + 1/Nf))}}$$

Equation 2
$$P = \frac{(Ns.Ps + Nf.Pf)}{(Ns + Nf)}$$

Where:

$Ns =$ the number of banks in the survivor group.
$Nf =$ the number of banks in the failure group.

Under the null hypothesis, the distribution of T can be approximated by the normal distribution. Column 4 of Tables B and F indicate where it is possible to reject the null hypothesis in a two-tailed test at three confidence intervals (90%, 95% and 99%) with *, ** and *** respectively.

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