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Abstract

This paper is based on a study of a number of new bank monitoring systems currently in use or under development in various G10 countries. Such systems are collectively termed “supervisory risk assessment and early warning systems”. The objective of the paper is to provide an overview of the different approaches taken by bank supervisors and to make a preliminary general assessment of the methods that are being used or developed. The study reveals that supervisory authorities are now clearly moving towards putting in place more formal, structured and risk-focused procedures for ongoing banking supervision. Individual approaches and systems have been developed and adopted, typically in the 1990s, with a greater focus on risk profiles and risk management capabilities of individual banking institutions and on the generation of timely warning of potential changes to a bank’s financial position. These new and modified systems have contributed positively to the supervisory process, and supervisors are working towards refining the systems further in order to improve the systems' accuracy and predictive power. It is expected that in the future, formal risk assessment and early warning systems will continue to be developed and adopted by bank supervisors in developed and emerging market economies for risk-based supervision and will contribute significantly to strengthening the process of ongoing banking supervision.

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Introduction[1]

Innovation, deregulation and globalisation in banking have contributed to making banking business more complex and potentially riskier. This has presented new challenges to bank supervisors with respect to the structuring of their ongoing supervision. In response, supervisors have developed new methods and processes for monitoring and assessing banks on an ongoing basis. Particular attention is being paid in this regard to improving the quality of bank examinations and to the development of systems that can assist supervisors and examiners in identifying changes, particularly deterioration, in banks' financial condition as early as possible. Amongst the various new initiatives that have been taken or are being taken in this respect are the development of more formal, structured and quantified assessments not only of the financial performance of banks but also of the underlying risk profile and risk management capabilities of individual institutions. Collectively these various new approaches can be termed "supervisory risk assessment and early warning systems".

This paper is based on a study of a number of supervisory risk assessment and early warning systems currently in use or under development in various G10 countries as part of a move toward risk-based supervision. The objective is to provide an overview of the different approaches taken by bank supervisors and to make a preliminary general assessment of the methods that are being used or developed. Section 1 of the paper sets out a simple framework for banking regulation and supervision in order to describe where and how the new systems fit into the process of banking supervision. Section 2 categorises the different approaches that can be found in G10 supervisory practices with respect to risk assessment and early warning systems. The various approaches, i.e. supervisory bank rating systems, financial ratio and peer group analysis systems, comprehensive bank risk assessment systems and statistical models are subsequently described, compared and analysed in sections three to six, respectively.

[1] Ranjana Sahajwala from the Reserve Bank of India was a visiting fellow at the BIS attached to the Secretariat of the Basel Committee on Banking Supervision and Paul Van den Bergh was Deputy Secretary General of the Basel Committee on Banking Supervision in 1999, when most of the background work was carried out. An earlier draft of the paper was presented at a Workshop on Supervisory Risk Assessment and Early Warning Systems organised by the Basel Committee and the Bank of England in March 2000. The authors gratefully acknowledge the comments of the various experts from supervisory authorities at the Workshop, including Steven Phillips (US Office of the Comptroller of the Currency), Han van der Hoorn and Iman van Lelyveld (Netherlands Bank), Michael Stephenson (UK Financial Services Authority), Andrew Logan (Bank of England), Daniel A Nuxoll and Katherine Samolyk (US Federal Deposit Insurance Corporation), Kevin Bertsch and Diana Hancock (US Board of Governors of the Federal Reserve System), Christopher Peter (French Banking Commission), and S Laviola, P Marullo Reedtz and M Trapanese (Bank of Italy). They are also grateful to Urs Birchler (Swiss National Bank and Chairman of the Basel Committee's Research Task Force) for encouragement and support. Thanks are due to Danièle Nouy (Secretary General), William Coen (Member of Secretariat), Lynn Kirman and Tracy Powell of the Basel Committee Secretariat for their assistance at various levels. The paper benefited from the discussions with Fred C. Herriman Jr., Jonathan Akeley, Patrick Guerchonovitch, Didier Blanchard, Donald Conner, William Francis, Robert Avery, Michael Gordy, George Hanc, Jack Reidhill, Gary Whalen, T. Schmidtz Lippert and Peter Lutz from various supervisory authorities. Comments on the paper may be sent to rsahajwala@rbi.org.in or paul.van-den-bergh@bis.org.

The paper concludes that the various approaches have all contributed positively to the supervisory process, and that supervisors are likely to work towards refining the systems further in order to improve their accuracy and predictive power. It is expected that in the future, formal risk assessment and early warning systems will continue to be developed and adopted by bank supervisors in developed and emerging market economies and will contribute significantly to strengthening the process of ongoing banking supervision.

1. A simple framework for banking regulation and supervision

There is no theoretically optimal system or standard textbook blueprint for the structure and process of regulating and supervising financial institutions, including banks. In fact, arrangements for banking regulation and supervision differ considerably from country to country. Apart from differences in political structures, the most important factors that account for the differences in regulatory and supervisory approaches include the general complexity and state of development of the financial system, the number, size and concentration of banking institutions, the relative openness of the domestic financial system, the nature and extent of public disclosure of banks' financial positions, and the availability of technological and human resources for regulation and supervision.

However, an implicit framework for the regulation and supervision of banks can be found in the *Core Principles for Effective Banking Supervision* issued by the Basel Committee on Banking Supervision in 1997. The framework can be interpreted as comprising four distinct yet complementary sets of arrangements:

- legal and institutional arrangements for the formulation and implementation of public policy with respect to the financial sector, and the banking system in particular;
- regulatory arrangements regarding the formulation of laws, policies, prescriptions, guidelines or directives applicable to banking institutions (e.g. entry requirements, capital requirements, accounting and disclosure provisions, risk management guidelines);
- supervisory arrangements with respect to the implementation of the banking regulations and the monitoring and policing of their application;
- safety net arrangements providing a framework for the handling of liquidity and solvency difficulties that can affect individual banking institutions or the banking system as a whole and for the sharing of financial losses that can occur (e.g. deposit insurance schemes or winding-up procedures).

With respect to the supervisory arrangements, the Core Principles describe what could be termed a "cradle to grave" approach covering the licensing of individual banks, the process of ongoing supervision and mechanisms for taking prompt corrective actions in case institutions do not meet regulatory or supervisory requirements (the latter would also include exit arrangements for institutions facing serious losses or default and the possible resulting activation of safety net arrangements). The overall objective of this comprehensive process of supervision is to guarantee that banks can be established, operated and restructured in a safe, transparent and efficient manner.

Ongoing banking supervision consists of a differentiated mix of off-site monitoring procedures and on-site examinations. Off-site monitoring is the minimum tool for ongoing supervision. Supervisory authorities, which do not have the mandate or resources to carry out periodic on-site examinations, rely extensively on this method to monitor the financial condition and performance of banks and to identify those institutions that may need closer scrutiny. The process involves analysing and reviewing periodic financial and other information received by the supervisor relating to banks' activities. Supervisors typically subject regulated banks to reporting requirements covering, for instance, balance sheet and profit and loss statements, business profile, loans, investments, liabilities, capital and liquidity levels, loan loss provisions, etc.

During on-site examinations, supervisors make an overall assessment of a banking institution on the premises of the organisation. Examinations by specialised and trained bank examiners allow a more hands-on assessment of qualitative factors such as management capabilities and internal control procedures that may not be reflected adequately in regulatory reports. Supervisory authorities may also commission outside organisations such as external auditors to undertake a full on-site examination or to review specific areas of operations within a banking institution. Of course, external auditors also conduct independently annual statutory audits of the accounts of a banking firm as well as the firm's compliance with accounting procedures and best practices. In principle, this should provide the supervisor with an additional assurance that the accounts of a bank provide a true and fair view of the bank's financial position. In many cases, bank examiners will pay particular attention to these audit reports and to the ways in which banks deal with recommendations formulated by their external auditors.

Over the last few years supervisors have adopted new approaches and developed new systems for ongoing banking supervision in order to be better equipped to face the many challenges presented by financial innovation and globalisation. These new systems seek to assess and track changes in a bank's financial condition and risk profile and to generate timely warning for the supervisor to help initiate warranted action.

2. Supervisory risk assessment and early warning systems

This paper examines the formal approaches towards supervisory risk assessment and early warning systems that have been developed recently and are currently in use or being developed in a number of G10 countries. Some other systems that were developed but subsequently not put to use, or used but subsequently discontinued for one reason or another are also mentioned briefly, to give an insight into their working and methodology. As can be seen from Table 1, which lists the systems studied, many supervisors implemented one or more systems for risk assessment and early warning during the 1990s. While some of the systems are able to provide *ex post* indication of existing problems, other systems try to generate *ex ante* warnings of potential problems that may emerge or develop in the future on account of the current risk profile of the banking institution. Overall, supervisory risk assessment and early warning systems assist in:

- Systematic assessment of banking institutions within a formalised framework both at the time of on-site examination and in between examinations through off-site monitoring;
- Identification of institutions and areas within institutions where problems exist or are likely to emerge;
- Prioritisation of bank examinations for optimal allocation of supervisory resources and pre-examination planning; and
- Initiation of warranted and timely action by the supervisor.

Table 1: Supervisory risk assessment and early warning systems in selected G10 countries

Country	Supervisory Authority	System	Year of implementation	System type
France	Banking Commission	ORAP (Organisation and Reinforcement of Preventive Action)	1997	Off-site Supervisory bank rating system
		SAABA (Support System for Banking Analysis)	1997	Early warning model - Expected loss
Germany	German Federal Supervisory Office	BAKIS (BAKred Information System)	1997	Financial ratio and peer group analysis system
Italy	Bank of Italy	PATROL	1993	Off-site Supervisory bank rating system
		Early Warning System	Planned	Early warning model - failure and timing to failure prediction
Netherlands	Netherlands Bank	(RAST) Risk Analysis Support Tool	1999	Comprehensive bank risk assessment system
		Observation system	Planned	Financial ratio and peer group analysis system
United Kingdom	Financial Services Authority	RATE (Risk Assessment, Tools of Supervision and Evaluation)	1998	Comprehensive bank risk assessment system
	Bank of England	TRAM (Trigger Ratio Adjustment Mechanism)	Developed 1995 – not implemented	Early warning model
United States	All three supervisory authorities	CAMELS	1980	On-site examination rating
	Federal Reserve System	Individual Bank Monitoring Screens	1980s	Financial ratio analysis
		SEER Rating (System for Estimating Exam Ratings)	1993	Early warning model - Rating estimation
		SEER Risk Rank	1993	Early warning model- Failure prediction
	FDIC	CAEL	1985 (withdrawn December 1999)	Off-site supervisory bank rating system
		GMS – Growth Monitoring System	mid 1980s (refined recently)	Simple early warning model - tracking high growth banks
		SCOR (Statistical CAMELS Off-site Rating)	1995	Early warning model - Rating downgrade estimation
	OCC	Bank Calculator	Planned	Early warning model Failure prediction

Just as approaches to banking regulation and supervision differ from country to country, approaches to supervisory risk assessment and early warning also differ in various respects depending upon country-specific factors. These include the extent, scope and frequency of on-site supervision; the off-site monitoring mechanism; the extent, nature and reliability of regulatory reporting; the availability of other reliable sources of information; the availability of historical data on bank distress and failure; the level of technological advancement; and the availability of necessary budgetary and human resources. It is possible, however, to group the various systems studied under four broad categories of formal approaches:

(i) *supervisory bank rating systems*;

(ii) *financial ratio and peer group analysis systems*;

(iii) *comprehensive bank risk assessment systems*;

(iv) *statistical models*.

An overview of the generic features of each approach category is provided in Table 2.

Table 2: Approaches to supervisory risk assessment and early warning systems – generic features

	Assessment of current financial condition	**Forecasting future financial condition**	**Use of quantitative analysis and statistical procedures**	**Inclusion of qualitative assessments**	**Specific focus on risk categories**	**Link with formal supervisory action**
Supervisory ratings						
- on-site	***	*	*	***	*	***
- off-site	***	*	**	**	**	*
Financial ratio and peer group analysis	***	*	***	*	**	*
Comprehensive bank risk assessment systems	***	**	**	**	***	***
Statistical models	**	***	***	*	**	*

* not significant

** significant

*** very significant

Supervisory authorities in G10 countries make use of more than one system for supervisory risk assessment, with the intention that problem institutions may be identified by at least one of the systems. The systems adopted generally combine elements of qualitative assessments and computer-assisted quantitative evaluations. In some systems, human assessments and qualitative judgements still play a dominant role; in other cases, human judgements are combined to a lesser degree with the output from the artificial intelligence of computer programs. The different categories of formal approaches to risk assessment and early warning are described and evaluated in more detail in the sections below.

3. Supervisory bank rating systems

Supervisory ratings of banking institutions were originally initiated as assessments derived on the basis of on-site examinations. Over the last few years, the approach has also been developed and applied to function on an off-site basis. Supervisory bank rating systems help identify institutions whose condition warrants special supervisory attention in both mandated and non-mandated examination regimes.

On-site examination ratings are based on subjective assessments by the examiner of various aspects of the functioning of a banking institution. Though the assessments are made against benchmarks that represent the essential foundation for the assessment, they are not rigorous and restrictive, and allow the examiner to consider other factors that he may find pertinent to his assessment of a banking institution. While on-site examination ratings may be shared with the management of the bank concerned, they are not made public.

Off-site supervisory ratings are based on off-site analysis of regulatory and other information available to the supervisor as well as information contained in on-site examination reports. These ratings are assigned on the basis of a continuous process of evaluation of a banking institution over a period of time, generally one year. Off-site supervisory bank ratings are generally confidential and used internally by supervisors.

Range of practices

In the 1980s, the US supervisory authorities, through the use of the CAMEL rating system, were the first to introduce ratings for on-site examinations of banking institutions. The concept introduced a uniform system of rating a banking institution in the United States. It is based on examiner assessment of a banking institution under certain supervisory criteria, and is used by all three US supervisory agencies, i.e. the Federal Reserve System, Office of the Comptroller of the Currency (OCC) and the Federal Deposit Insurance Corporation (FDIC).[2] Under this system, each banking institution subject to

[2] In the United States, banks are supervised by different agencies depending on their charter. The OCC supervises nationally-chartered banks. State-chartered banks that are members of the Federal Reserve System are supervised by the Federal Reserve and the FDIC supervises state-chartered banks that are not members of the Federal Reserve System.

on-site examination is evaluated on the basis of five (now six) critical dimensions relating to its operations and performance, which are referred to as the component factors. These are Capital, Asset Quality, Management, Earnings and Liquidity and are seen to reflect the financial performance, financial condition, operating soundness and regulatory compliance of the banking institution. In 1996, in an effort to make the rating system more risk-focused, a sixth component relating to Sensitivity to market risk was added to the CAMEL rating, making it CAMELS. Each of the component factors is rated on a scale of 1 (best) to 5 (worst).

A composite rating is assigned as an abridgement of the component ratings and is taken as the prime indicator of a bank's current financial condition. The composite rating ranges between 1 (best) and 5 (worst), and also involves a certain amount of subjectivity based on the examiners' overall assessment of the institution in view of the individual component assessments. Details on CAMELS on-site rating system methodology are given in Annex 1.

CAMELS ratings are normally assessed every year as every banking institution in the United States is generally examined once a year. In the case of problem banks (those with a CAMELS rating of 4 or 5), the ratings may be assessed more frequently, as these banks are subject to more frequent on-site examination. Conversely, in the case of sound banks (those with a CAMELS rating of 1 or 2), on-site examinations may be conducted after an interval of 18 months, and the ratings would accordingly be updated once every one and a half years.

The on-site examination ratings assigned by the US supervisory authorities are treated as the most significant and reliable tool for assessing the current financial condition of a banking institution. They also form the basis for determining causal relationships between financial ratios calculated through off-site analysis and the actual rating assigned after an on-site examination. Accordingly, this forms the basis for some of the US supervisors' early warning models described later in this paper in Section 6 – Statistical models.

The Federal Reserve, which is also responsible for supervising bank holding companies (BHCs), uses the BOPEC on-site examination rating system for rating BHCs. The BOPEC rating is derived from the five components of BOPEC, i.e. Bank subsidiaries covered by the bank deposit insurance fund, Other subsidiaries, Parent company, Earnings and Capital, plus a separate management rating. Each BOPEC component rating is scaled from 1 (best) to 5 (worst). The five component ratings are then converted to a composite rating also scaled from 1 (best) to 5 (worst). Management is assessed separately and can be rated only at three levels as satisfactory, fair or unsatisfactory.

One US supervisory authority, the FDIC, developed and adopted a quarterly off-site supervisory rating system, CAEL, in the mid-1980s. The system has since been withdrawn with its last run concluding in December 1999. CAEL was an expert system making use of simple ratio analysis to assign a quarterly off-site rating to a banking institution. It used financial ratios from call reports[3] to rate institutions on a scale of 0.5 (best) to 5.5 (worst).

The CAEL off-site rating system referred to four of the five CAMEL component ratings in existence at the time of its introduction, i.e. Capital, Assets, Earnings and Liquidity. The Management component was not part of CAEL as there was no off-site information available for assessing the management of a banking institution. Calculation of CAEL ratings involved 19 financial ratios representing the four main component categories.

The system divided banks into peer groups based on asset size, and calculated percentile rankings for four sets of financial ratios corresponding to the four component ratings. Each of the four component ratings was calculated as a weighted average of a corresponding set of financial ratios. The composite CAEL rating was calculated as a weighted average of the four component ratings. A panel of bank examiners determined the ratios to be used in calculating the ratings and the weights associated with each ratio. The estimated CAEL rating was compared with a bank's most recent prior on-site CAMELS rating. If the off-site CAEL rating was worse than the prior actual on-site rating, the bank was flagged for further review.

The CAEL system was built with a specific bias towards downgrading institutions. Without the bias, an institution receiving a CAEL 2.5 could obtain a subsequent on-site examination rating of either 2 or 3. But the CAEL bias meant that the institution rated 2.5 in CAEL was more likely to get a next examination rating of 2. Expectedly, the bias led to CAEL flagging more institutions as likely to develop problems, as compared with the number of institutions that did actually develop problems, and carried a very high Type II error.[4] CAEL has now been replaced with a statistical model discussed later in this paper.

The supervisory rating system as a tool for evaluating the current financial condition of a bank has since been adapted and adopted by supervisory authorities in some other countries, including Italy and France, to be used on an off-site basis. In these countries, annual ratings are assigned on the basis of off-site reviews and analysis of other available quantitative and qualitative information, and comprise more or less similar component factors to those of the US on-site rating system. As with the US on-site ratings, these off-site supervisory ratings incorporate a considerable amount of human judgement guided by supervisory criteria for each component of the rating.

[3] A call report is the quarterly regulatory reporting information submitted by banks in the United States. Call report data form the main input for all off-site monitoring systems in the United States.

[4] A Type II error is a statistical term identified with misclassification by a model. In the context of identifying weak and strong banks, it denotes that a system wrongly classifies a strong bank as a weak bank. Conversely a Type I error represents a misclassification of a weak bank as strong. This is discussed in more detail in Section 6 – Statistical models.

The Bank of Italy has introduced the annual PATROL rating system in 1993 as an off-site supervision tool to give a systematic representation of the financial health of individual banks and provide support in prioritisation of the use of supervisory resources in scheduling on-site examinations. As there is no specific mandate for periodic on-site examinations of banking institutions in Italy, they are undertaken based exclusively on evidence provided by the whole set of information available for analysis to the supervisor for assigning PATROL ratings.

The main inputs for the PATROL off-site analysis include information from monthly, semi-annual and annual regulatory reporting data received by the Bank of Italy. Additional inputs include central credit register data maintained within the central risk division of the Bank of Italy regarding individual bank loans above 150 million lire. Other inputs include information on firms from the company accounts data service, the latest onsite examination information and any other information that may be available to the analyst.

The five components of PATROL are capital adequacy, profitability, credit quality, organisation and liquidity. Capital adequacy is assessed by comparing the own funds of a bank with regulatory prescriptions of capital for credit risk, position risk, settlement risk, market risks and exchange rate risk. To assess profitability, the economic results net of extraordinary items are related to the requirement to cover capital losses stemming from bad debts, and the return on equity is related with the average of the banking system. The interest margin is also taken into account. Credit quality is assessed on the basis of aggregate data of adjusted bad debts[5] derived from the central credit register and an individual loan concentration index. The organisation component is assessed on the basis of ad hoc information available to the analyst, on information obtained from meetings held with the management of banks and on-site examination results. Liquidity is assessed after ascertaining maturity mismatches under normal operating conditions, and by simulating exogenous shocks over a one-year time horizon. Two stress scenarios are also simulated which include a sudden outflow of customer and interbank deposits and an increase in the share of used credit facilities on behalf of borrowers, to see how the bank would perform under adverse conditions.

Each component of PATROL is rated on a scale of 1 (best) to 5 (worst) based on supervisory criteria and guidelines. Five individual component ratings are converted into a composite rating, also on a scale of 1 (best) to 5 (worst), which includes all other quantitative and qualitative information available to the analyst. Ratings assigned are validated through comparisons with the actual results of on-site examinations.

[5] Adjusted bad debts include all loans classified as such when the bank is the only lender plus those loans to customers with multiple lending relationships when a significant share of the overall exposure is classified by remaining lenders as bad debt; in this case, the bank customer is considered insolvent irrespective of the individual bank's assessment.

Even though the final assessment makes use of both qualitative and quantitative information available to the analyst in the current year, the quantitative assessment mainly relates to data for the previous year and the rating itself is available only with a considerable time lag. It should also be noted that PATROL ratings only reflect the condition of the banking institution at a point in time and therefore are highly responsive to changes in bank performance and economic conditions related to business cycles. In particular, the ratings are found to be highly variable in the case of banking institutions previously rated 3.

The French Banking Commission introduced the annual Organisation and Reinforcement of Preventive Action (ORAP) rating system in 1997 as a multi-factor analysis system for individual institutions. The objective of the system is to detect potential weaknesses in banking institutions by examining all components of risk associated with the activity and environment of each institution making use of quantitative and qualitative information.

The ORAP rating makes use of various internal and external sources of information. These include different databases of the Bank of France and the Banking Commission (in particular the data provided by the credit institutions themselves, which are stored in a special financial markets database), as well as results of on-site supervisory inspections. The external sources include external auditors, other supervisory bodies in France and information made available under bilateral arrangements with supervisory bodies in other European countries.

The system works within a standardised and formalised framework, with specific ratings on 14 components. The components relate to prudential ratios (capital, liquidity, large exposures and capital adequacy), on- and off-balance sheet activity (asset quality, bad loans and provisions for bad loans), market risk, earnings (operating income, non-recurring items and return on assets) and qualitative criteria (shareholders, management and internal control). Each component is rated on a scale of 1 (best) to 5 (worst). Component ratings are converted to a composite rating similarly scaled between 1 (best) and 5 (worst). Every 5 rating implies corrective action.

At the Netherlands Bank, until the end of 1999, annual off-site ratings were assigned by supervisors based on their assessment of a banking institution in the context of the information made available to them from various sources. These sources included monthly and quarterly regulatory reporting data, annual accounts, on-site examination reports and any other available information. Ratings were assigned based mainly on professional judgements of supervisors, following some general guidelines laid down by the Netherlands Bank in this regard. In view of the potential for human error in qualitative assessments, the ratings were subjected to review by another supervisor under the four eyes principle. The rating system has recently been replaced by a risk assessment system, described later in Section 5 – Comprehensive bank risk assessment systems.

Issues

On-site examination ratings are effective tools in assessing the current financial condition of a banking institution and identifying existing problems. They provide a reference point for the financial condition of a banking institution but, as the indications obtained relate to problems in banking institutions that are mainly *ex post*, rating assessments may remain relevant only for short periods of time.

On-site examination ratings are not specifically designed to track changes in financial condition, and may start to decay shortly after the examination process is complete. This is more pronounced in the case of banks already in financial trouble, as well as in periods of banking industry stress. Studies in the United States have shown that while on-site examination ratings have the advantage of incorporating confidential supervisory information along with regulatory and publicly available information, the value of this information content may begin to decay two quarters after the examination process is complete. On-site examination ratings available at any given date are as at the last on-site examination. Thus, even if all banks are examined once each year, the ratings available at any one time are generally six months old. This is, in fact, the beginning of the period over which the usefulness of the information of on-site examination rating begins to decline.

On-site examination ratings like CAMELS are useful in the analysis of the financial condition of the bank at the time of the examination, its compliance with regulatory policies, the accuracy of the regulatory reporting, the quality of its management, the loan loss recognition, and the internal controls practised, as well as in detecting financial misconduct. Ratings can be accurate indicators of potential problems only if banks are examined at frequent intervals and their financial conditions generally remain stable. Examinations are, however, carried out with some time lag and, insofar as financial conditions of banks can and do change rapidly, supervisory on-site examination ratings cannot be expected to function as condition indicators of banks for long periods of time, much less to serve as early indicators of future problems.

Off-site supervisory ratings that are based mainly on information available through regulatory reporting can, by comparison, track the changes in the financial condition of banks, as the off-site information flow is more frequent than actual on-site field examinations. This was reflected in the CAEL off-site rating of the US FDIC, which was based on quarterly call report data and was updated every quarter. In the case of France and Italy, annual supervisory off-site ratings are a culmination of a continuous assessment of a banking institution over a period of time. The assessment is based not only on the analysis and review of regulatory reporting data, but also on annual accounts, on-site examination reports and any other information available to the supervisor. Though based on continuous assessments carried out over the year, the annual ratings can still be construed as backward-looking as they mainly refer to the prior year’s financial data of the banking institution, albeit viewed in conjunction with some current qualitative assessments. Since on-site examinations are not specifically mandated for a prescribed frequency in these countries, as in the United States, the annual off-site ratings may still represent a more frequent assessment of bank financial condition than an on-site examination, and provide a reference point for future assessments.

In summary, supervisory bank ratings are not forward looking or specifically designed to distinguish banks likely to fail from banks likely to survive in the future. Rather, they generally provide *ex post* indications of problems existing in banking institutions. Supervisors use ratings mainly to identify banks that may need immediate or special supervisory attention.

4. Financial ratio and peer group analysis systems

It is generally acknowledged that banks' financial condition can be related to a fairly consistent set of financial variables. These variables mainly include measures of capital adequacy, asset quality, profitability and liquidity. Not surprisingly, a large number of ratios relating to these variables are used in various financial ratio and peer group analysis systems. These frameworks are also termed "general expert systems" for their use as distinct, stand-alone risk assessment systems. The term also relates to their use in varying degrees in many of the systems grouped under the other approach categories, and the artificial intelligence that is used to replicate the financial analysis that an examiner would perform on-site within a banking institution.

The input for the systems is based to a large extent on regulatory reporting data and annual accounts. The analysis undertaken is used to make past performance comparisons for individual banking institutions, and also for setting benchmarks of financial performance for different "peer groups" in order to identify outlier banks.

Financial ratio analysis for individual institutions generates a warning if a ratio exceeds a predetermined critical level, or lies within a set interval, or is an outlier as far as the past performance of the bank is concerned. Peer group analysis is undertaken on the basis of financial ratios for a group of banks taken together. It is used to ascertain whether an individual bank is performing in a significantly different way from its peers and the reason for such significant difference, which may or may not imply supervisory concern.

The constitution of peer groups in systems under this approach category is generally done on the basis of asset size (e.g. small versus large banks) or on the basis of specific segments of the banking industry (e.g. domestic commercial banks, foreign banks, cooperative banks or savings banks). Some of the systems now also allow the line supervisor to construct a customised peer group for comparisons (e.g. banks belonging to a particular geographical region or business line). Each bank's individual ratios are compared with the peer group to which it belongs. Within each peer group, either a simple identification of the worst performers as compared to the peer average is made or the financial ratios are sorted from best to worst, and percentile rankings are calculated. Individual banks whose financial ratios have deteriorated relative to the averages of their respective peer group can then be identified.

Financial ratio and peer group analysis is also used to examine trends in the banking sector as a whole, or in particular segments of the banking sector, and to carry out a systematic analysis across the selected field. It is also used in a limited manner for performing stress testing and scenario analysis, e.g. the expected condition of banks under adverse financial conditions or different economic situations.

Range of practices

US supervisory authorities have been using off-site computerised surveillance screens since the late 1970s for initial identification of likely problem institutions. These surveillance screens allowed supervisors to analyse systematically, every quarter, various data reported by banks in the call reports. The analysis undertaken pertained to some ratios that were commonly used during examinations, those that were familiar to the bank examiner and banker alike and were well understood. However, the simple ratio analysis did not function effectively and frequently flagged either too many banks or the wrong banks.

More recently, in the late 1980s the Federal Reserve developed individual bank monitoring screens to undertake detailed financial ratio analysis of individual banks and to serve as primary filters of potentially problematic banks. The screens consist of a series of tables that report selected financial data and ratios for each institution. Those institutions with ratios falling outside preset thresholds or showing significant change over their own past performance are identified as “exceptions” and subjected to additional supervisory review.

More than 30 financial measures of supervisory interest are represented on the monitoring screens that are run every quarter based on call report data. Many of these correspond closely with areas specifically considered in assigning on-site CAMELS ratings. Many others are designed to flag new activities. Additionally, several measures relating to monitoring capital markets are surveyed in the case of banks undertaking capital market activities. The ratios measure changes in total assets, changes in non-current assets, changes in capital, loan concentrations under commercial loans, consumer loans, residential real estate, commercial real estate, liquidity, trading revenue losses, dividend payouts, salary expenses, insider loans, derivatives credit risk, credit derivatives etc. Individual bank monitoring screens play an important role in targeting areas that evidence potential weakness or significant change and thus help undertake more focused examination planning. In addition, they provide a very useful context for interpreting, in detail, the results of the SEER[6] statistical models used by the Federal Reserve.

The BAKred[7] Information System (BAKIS) implemented in 1997 is a comprehensive and standardised supervisory information system shared by the supervisory authority and the German central bank. It uses financial ratio and peer group analysis as a risk assessment component within the system. Subsequently, the system is expected to specifically include an early warning system for identifying problem banks.

The current BAKIS system makes use of monthly and quarterly regulatory reporting data, and annual accounts as the input data. The objectives of the system are to make a quick assessment of a bank's financial situation, early detection of trends and possible accumulations in credit risk, market risk and liquidity risks, and observation of general developments within banking groups or the entire banking sector.

A total of 47 ratios relating to risk factors and profitability are analysed monthly, quarterly, semi-annually or annually to assess the risk-bearing and risk-taking capacity of individual banking institutions. The risk factors are represented in 19 credit risk ratios (including solvency), 16 market risk ratios and 2 liquidity risk ratios. This is complemented with 10 ratios relating to profitability. All the ratios are weighted equally in the system. The rationale for using a high number of ratios and assigning them equal weights is based on a twofold analysis of the ratios, first by checking for correlations between the ratios, and secondly by comparing the estimates of the BAKIS system with the estimation by a line supervisor. The analysis reveals that all ratios are equally important in ascertaining the overall financial position of a banking institution, and that none can be treated as redundant.

The system can be used to review individual bank ratios, or ratios by risk category within a peer group at any given point in time, as the ratios are calculated on a daily basis with the percentage of ratios calculated per group indicated on the screen. Comparisons of individual bank ratios can be made with those of the standard peer group. Some standard peer groups are already computed within BAKIS, but other combinations for peer group comparisons can be devised within the system. The individual bank ratios may fall within any of the five predetermined quintile classes ranging from best to worst. The use of the system in the supervisory process is currently restricted to prioritisation of supervisory activities based on bank risk profiles. The system does not include any trigger function for

6 The System for Estimating Examination Ratings (SEER) consists of two econometric models - the rating model and the risk rank model, detailed in Section 6 – Statistical models.

7 An acronym for the Bundesaufsichtsamt für das Kreditwesen - the Federal Banking Supervisory Office of Germany.

prespecified supervisory actions. The ratios and peer group ranks calculated in the system are not provided to the banks though the general trends revealed through the ratios are discussed with bank management.

At the Netherlands Bank financial ratio and peer group analysis is used in an "observation system" consisting of three modules for generating warnings. The supervisory authority was initially interested in constructing an early warning model to forecast probable failure. However, due to insufficient data on bank failures, it was found difficult to do so. As an alternative, development of a forecast system based on estimating bank ratings was attempted. However, as the bank rating system that was in use until December 1999 functioned under general guidelines and was hence somewhat subjective, and in view of the small and heterogeneous sample of banks available, it was difficult to construct an accurate model for rating estimation. The bank now plans to implement the "observation system" with the objective of generating warnings when financial ratios are statistical outliers.

The input for the Dutch system consists of key performance indicators culled from regulatory reporting and annual accounts, market information like external ratings and share prices where available, and macroeconomic data like interest rates and growth rates of GDP and industrial production. The frequency of the calculations and comparisons under the three modules could be daily, monthly, quarterly or semi-annual, depending on the ratio. A total of 53 ratios measuring growth or absolute levels are used in the system. Some ratios are included for information only and are not meant to generate a warning. Such ratios may be equal for all banks (e.g. macroeconomic variables), or may be warnings in themselves (e.g. credit ratings).

In Module I, a financial ratio of a bank is compared with its own past ratio. The peer group analysis comprises Modules II and III. Module II compares the present financial ratios of a bank with the present and past observations from the peer group. The user can determine whether he wants to compare the banking institution with a default peer group (largest banks, other domestic banks, subsidiaries of foreign banks, branches of foreign banks, securities investment firms), all other banks, or any other user-defined peer group. Since within a default or user-defined peer group a bank might be systematically different from its peer group, it is likely that just relying on Module II may lead to flagging too many banks. Module III is used for making peer group comparisons while accounting for systematic differences between banks. In this module, outliers are detected by comparing the difference between a bank's present ratio and its present peer ratio with the historical difference between a bank's ratio and peer ratio. Each of the modules is treated and shown independently in the system. It is therefore possible that different modules generate conflicting indications about a banking institution. In such a situation, the supervisor will have to decide which comparison is most appropriate.

The modules are expected to identify any bank that is performing significantly differently either from its own past performance or from its peers, warranting an explanation. Default statistical critical levels in the system have been set based on confidence intervals of 80% indicating some problem, and 95% indicating a highly likely problem. The supervisor will, however, have the flexibility to change the parameters for each ratio or criterion should the system generate too many or too few warnings. Critical values are set as one-sided. Also, there are absolute triggers, e.g. for the 8% Basel capital ratio.

The Risk Assessment, Tools (of supervision) and Evaluation (RATE) framework, developed as a comprehensive bank risk assessment system by the Bank of England and implemented by the UK Financial Services Authority (FSA) in 1998, also makes use of key ratio trends and peer group analysis during the formal risk assessment phase of a banking institution. This facilitates a current assessment of the bank's record in managing some key business risks including credit risk, market risk and liquidity risk. The system is described in more detail in Section 5 – Comprehensive bank risk assessment systems.

Issues

Financial ratio and peer group analysis is seen as a valuable complement to bank examinations. This approach has always been part of the off-site monitoring process as a basic minimum tool of ongoing supervision. However, in the last few years it has evolved from being a simple off-site calculation of some of the main financial ratios implicit in the on-site examination process to a formal risk assessment tool that uses a varied and high number of ratios in statistical formats. It is now specifically used to analyse the risk profile of a banking institution. One supervisory authority, the US Federal Reserve, also uses it as a complement to its statistical models, to be better able to interpret the output of the early warning models.

It is generally recognised, however, that financial ratio and peer group analysis is not sufficient on its own to identify the complex nature of risks undertaken by banks, particularly large banks and specialised banking institutions. Ratios are selected from a large set of variables and the extent of their correlation with an institution's financial condition may not always be significant enough for their inclusion in the systems. Weights assigned to each of the ratios can also prove to be a limitation. They may be determined on the basis of examiner experience, once assigned they may remain fixed and may fail to adjust for temporal shifts rendering the assessment inefficient.

Peer group analysis measures a bank's performance relative to that of other banks of similar size and activity. Systemic changes, in the performance either of peer groups of banks, or of the banking system as a whole, are not accounted for in the outputs. Thus, if an entire peer group deteriorates, the percentile scores of individual banks within that peer group may not change, even though the banks have become riskier. Conversely, when a change in the size of an institution places it in a larger or smaller peer group, the institution's percentile scores may change significantly, even if its underlying financial condition has not changed.

As this approach is based on an analysis of a large number of ratios it is possible to use this approach category to undertake various aggregations for the banking sector as a whole, or for various segments, as well as to undertake stress tests.

Financial ratio and peer group analysis is extensively and almost exclusively based on the data reported under regulatory reporting and annual account data. The integrity, timeliness and processing of data as well as sound accounting practices are a precondition for the analysis to be effective under this approach.

5. Comprehensive bank risk assessment systems

As the categorisation suggests, this approach makes a comprehensive and detailed assessment of the risk profile of a banking institution as a whole. The approach entails a disaggregation of a bank or banking group into significant business units and assessing each unit for all business risks, internal structures and controls based on a number of specific criteria. Scores are assigned for each assessment criterion. Individual scores and assessment results are aggregated consecutively to the next higher level to ultimately arrive at a final assessment or score for the banking institution or group. This approach has been developed and adopted recently by two G10 supervisory authorities.

Range of practices

In the United Kingdom a formal and comprehensive risk assessment of individual banks is a part of the RATE framework introduced by the Bank of England, and currently used by the Financial Services Authority.

The objective of the framework is to increase the effectiveness of supervision by making it risk-focused, and to have a systematic approach to ongoing dynamic supervision. It is used to determine customised supervisory action for an individual banking institution based on a systematic risk assessment, and to determine the intensity of supervision based on the score assigned to the institution. The system is applied to all UK-incorporated banks and the UK branches of non-EEA banks.[8]

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[8] UK branches of EEA-incorporated banks are not subject to RATE since the primary responsibility for their supervision lies with the home country supervisor.

The framework is based on the concept of determining a supervisory period for each individual institution, during the course of which the key elements of RATE are addressed and implemented. The supervisory period ranges from six months to three years depending upon the risk profile of the institution. However, evaluations of material changes that could affect the assessment, the progress by the bank on the action plan and the progress with the supervisory objective are undertaken annually for each institution.

The key elements of RATE include:

- Identifying significant business units on the basis of thresholds set for use of group regulatory capital/contribution to group revenue or profits/financial exposure as a percentage of bank capital;
- Obtaining pre-visit information from other regulators, in particular overseas home or host country regulators, to avoid duplication of work they have already performed;
- Planning the on-site work and undertaking on-site visits comprising meetings with bank management, heads of significant units and other key areas (e.g. internal audit, risk management, compliance, etc.);
- Undertaking detailed assessment of each significant business units' risk on the basis of quantitative and qualitative assessments using the CAMELBCOM factors (as discussed below);
- Devising a customised supervisory programme based on the assessment;
- Internally reviewing RATE assessments, which includes senior personnel within the Financial Services Authority reviewing the assessments for consistency and reasonableness, and for identifying trends and common issues;
- Assuring the quality of the RATE assessment by focusing on the extent to which internal processes have been followed by line management; and
- Providing feedback to the bank, its head office, its home country supervisor, other material regulators and the reporting accountants of the bank.

Formal risk assessment of significant business units is done on the basis of nine evaluation factors of the business risk profile of a banking group. The risks of each business area are evaluated on the basis of six factors, CAMEL-B. This reviews Capital, Assets, Market Risk, Earnings and Liabilities, and Business. The Business factor includes the bank's overall business and external environment, including a forward assessment of some of the risks analysed under CAMEL, and captures those risks that are not quantifiable such as operational, legal and reputational risk. In addition, a qualitative assessment of internal controls is undertaken using the three factors Controls, Organisation and

Management (COM). This analysis is done using the knowledge that the supervisor has acquired from its own on-site and off-site surveillance activities.

The assessment of each of the nine factors for the whole institution or group is converted to a numerical rating. From the nine numerical ratings a single score is derived, which represents the final RATE score for the institution. Though RATE scores are not divulged to the banking institutions, the assessments indicating the level (high, medium or low) and direction (increasing, stable or decreasing) of business and control risk are intimated to and discussed with the bank, its parent and other regulators concerned.

The assessment of a bank's current risk profile is supplemented by an assessment of likely changes in the profile over the next period. This assessment is made using the information already available to the supervisor, together with the supervisor's own forecast of the market.

For each institution, a suitable supervisory programme is devised and specific tools are identified. The latter include: obtaining from the bank important documents relating to management information, policy statements, full-scope or specific area reports by the bank's external auditors; undertaking special visits by the supervisory "traded markets" team to assess the treasury areas of the bank, or visits by the supervisory "review team" to assess other areas; and holding prudential and ad hoc meetings with the senior management of the bank. The results and effectiveness of the supervisory tools used are always carefully evaluated in an ongoing process.

A similar approach for comprehensive bank risk assessment has been developed and put to use by the Netherlands Bank in 1999 in the form of the Risk Analysis Support Tool (RAST). The risk assessment is conducted formally making use of specific and well-established criteria for each risk assessment category.

The risk analysis envisaged under the system involves four distinct stages: (i) a general description and financial analysis of the institution, based on the latest on-site examination reports and various data collected under regulatory reporting; (ii) breakdown of the institution into significant management units and functional activities; (iii) assessment of risks and controls in individual units; and (iv) aggregation of scores and reporting. All the significant units identified are assigned weights according to their significance (not riskiness). This is determined based on each of the unit's contribution to real or budgeted earnings. The weights are associated with three categories of significance - small, medium and large.

The risk assessment categories relate to the following risks: credit risk, price risk, interest rate risk, foreign exchange risk, liquidity risk, operational risk, IT risk, strategic risk, legal and integrity and reputational risk. The three control categories assessed are internal controls, organisation and management. All risk and control categories are assigned weights according to a default matrix, which the supervisor, however, can overrule.

All assessments are on a four-point scale with 1 representing low risk or strong controls (best) and 4 representing high risk or weak controls (worst), in the risk and controls categories, respectively. The aggregation is based on a mathematical algorithm, designed to reflect two issues, i.e. good and bad scores should not average out, and high risks are potentially more problematic than weak controls. The aggregation follows a bottom-up aggregation of individual risk and control risk assessment scores from the significant unit or functional activity level.

The individual supervisor is required to verify the computed scores and compare the outcomes against his professional judgement. The supervisor can manually overrule all computed scores at any level with appropriate justification. However, in order to achieve quality assurance during the entire risk assessment process, at least two experienced supervisors are involved in the different stages of the entire process.

In the final step, the overall outcome of the risk assessment of the institution as a whole is compared to its financial strength in terms of solvency (capital ratio) and profitability (return on equity). This final analysis is used to plan the supervisory review process for each individual institution. The scores of risk analysis including the overall rating are not communicated to the banks.

In the case of large banks, the supervisor may also mandate self-assessment in specific risk areas, using the RAST software supplied. The assessment made by the bank is then compared with the supervisor's assessment, and deviations are discussed with the bank.

While the comprehensive risk assessment approaches adopted by both the UK FSA and the Netherlands Bank are rather similar, there are a few significant differences. The aggregation methodology followed under RATE relates to aggregation by risk category for the whole organisation. In contrast, RAST follows aggregation by business unit or functional activity. Furthermore, while RATE makes use of capital and earnings as specific risk components, RAST merely makes use of them as quantitative figures, which are compared with the final score of the assessed institution at the end of the assessment.

Issues

This approach involves a comprehensive assessment of qualitative and quantitative risk factors in a banking institution. It entails interaction with other domestic and foreign supervisory authorities that may be additionally supervising the banking institution, which gives a well-rounded perspective of the banking institution/group. It is also the only approach that can be made applicable on a consolidated as well as unconsolidated basis to a group or individual institution.

While the final scores may not be divulged to the banking institution, the assessments made are discussed with them, which is advantageous for the supervisor and the supervised institution. The supervisor gains a better understanding of the quality of management and the business characteristics of each banking institution and its corresponding risk profile through the ongoing assessment. This enables the supervisor to undertake focused supervision, display more consistency in carrying out its supervisory responsibilities, and assess more systematically whether a bank continues to meet the minimum specified regulatory criteria for authorisation. Banks also benefit from an improved focus of supervision, and from a more specific targeting of tools of supervision at the areas of greatest risk and concern.

While the approach may be resource intensive and time consuming, its advantage lies in the fact that it may be well suited to large domestic as well as internationally active banks and banking groups undertaking diverse business activities. The risk profile of these organisations may not be easily apparent from the systems covered under the other approach categories.

6. Statistical models

The design and use of statistical models for predicting future bank health has been a significant development of recent years. Statistical models aim at being true "early warning models". They are essentially data-driven and use advanced quantitative techniques that attempt to translate various indicators of bank strength and performance into estimates of risk. Based on these estimates, the models try to segregate banks with a high risk of failure in the future from those with a low risk of failure in the future.

The development of statistical models to predict future bank health gained ground in the early 1990s. This was essentially a consequence of the spate of bank failures experienced in the United States, the accompanying cost of resolution and the possibility of triggering systemic risk inherent in such failures.

There are two essential differences between statistical models and the three approaches described earlier. First, the focus of statistical models is directed mainly towards the detection of risks that are likely to lead to adverse future conditions in a banking institution. Statistical models attempt to identify high-risk banks reasonably in advance of distress or failure. This stands in contrast to the focus on current conditions of a banking institution, which is by and large the main objective of the other three approaches.

Secondly, models use advanced quantitative techniques to determine causal economic relationships between explanatory variables and outcomes such as bank fragility, distress and failure or survival. The existence and impact of various causal factors is tested for specific outcomes. Quantitative measures of the direction and strength of causality are produced, and statistical inference is used as a guide to determine the properties and characteristics of the causal relationships. These are then used to predict future events having similar characteristics. To date, qualitative factors have not played a significant role in statistical models. By contrast the first three approach categories, while using quantitative analysis in varying degrees, rely extensively or in part on human judgement. This is true not only in the selection and choice of the explanatory variables and their weights but also at times for making a final assessment of the quantitative result.

Various estimation techniques may be used to construct statistical models. Most of the models studied and covered in this section are based on the qualitative response technique that analyses a causal relationship between a set of limited dependent variables and certain independent variables. The dependent variables in these models could be failure or survival, or ordered outcomes like bank ratings. This contrasts, for instance, with a macroeconomic model that forecasts gross domestic product, where outcomes may take on unlimited values. The estimated probabilities of the dependent variables are at some unspecified point in time, but over an interval implied by the model.

One of the models covered in this section is expected to be based on the duration technique, which is used to generate estimates not only of the probability of failure of a bank, but also of the probable time to failure. In such a model, which assumes that every bank will ultimately fail, the dependent variable is not just “failure” but “time to failure”. The model constructs an equation that allows calculation of the probability that a bank with certain specific characteristics will survive longer than some specified time into the future, or fail at a specified time in future, where the time can vary over a range of values.

Range of practices

Currently, only the US and French supervisory authorities make use of statistical models. In the United States two supervisory authorities, the Federal Reserve and the FDIC, make use of one or more statistical models as part of their extensive off-site monitoring process. To estimate some of their early warning models, these supervisors have drawn upon the existing historical data with regard to large-scale bank failures that occurred in the United States in the 1980s and early 1990s. The French Banking Commission has drawn upon the long-standing database on individual credits and the statistical analysis by the Bank of France to construct its statistical model. The OCC and Bank of Italy are currently developing and testing their respective early warning models for implementation shortly.

While the methodology of the models in use or under development is diverse, for the purpose of analysis, a number of models are grouped under the same generic heading in this section. The broad classification is as follows: (a) models estimating ratings or rating downgrades, (b) failure or survival prediction models, (c) expected loss models and (d) other models.

Table 3 gives the comparative features of selected early warning models.

Table 3: Comparative features of selected statistical early warning models

Model	Objective	Time horizon	Frequency	Inputs	Methodology	Use of human judgement	Output	Uses of output
SAABA – expected loss model **Banking Commission, France**	Assessing future solvency based on potential losses in credit portfolio	3 years	Every 6 months	Regulatory reporting data Internal assessments of legal, country and sector risks Bank of France database and analysis of corporate risk and default External rating agencies	Assessment of expected losses in credit portfolio over 3 years Adjustment of potential losses from current capital and future profitability Assessment of management and shareholder commitment	Yes, for assessment of management quality and shareholder commitment in the final analysis	Listing of all institutions under 5 categories Detailed analysis of each institution	Supervisory department for surveillance On-site examination department to plan exams Banking System General Supervision Department for aggregations for banking sector trends
SEER risk rank – failure prediction model **Federal Reserve System, US**	Predicting probability of failure	2 years	Every 3 months	Quarterly call report data	Bivariate probit regression Assessing current characteristics of bank financial variables for similarities with model variables (estimation period 1985–91)	No	Exception listing of banks that fail criteria - risk rank of 2–3% or more Risk profile analysis of each bank giving “change analysis” and “peer analysis”	Greater surveillance of exception banks Observe general movement and trend of exception listed banks
Growth Monitoring System – growth tracking model **FDIC, US**	Identification of potentially risky banks	4–5 years	Every 3 months	Quarterly call report data	Identification of banks with loan growth rate of more than 5%, based on 4 ratios and 5 growth rates	No	Flagging of high growth banks	Greater surveillance of banks flagged

Table 3 (cont'd)

Model	Objective	Time horizon	Frequency	Inputs	Methodology	Use of human judgement	Output	Uses of output
Bank Calculator – failure prediction model **OCC, US**	Identify banks at risk of failure, and overall risk of failures before any other indication of risk is available. The identification should precede examiner downgrades	1 year (3 years also being tested)	Annual	Annual data Other information - county unemployment rate	Assessment of 3 main risk categories: Bank portfolio risk (liquidity, troubled loans, prior CAMELS) Bank condition risk (earnings and capital) Bank environment risk (county/state unemployment rate, bank size, age of bank charter, regulatory regime shifts)	No	List of banks at risk for examination staff Overall risk of bank failures	Greater surveillance

(a) Models estimating ratings or rating downgrades

Two of the US Supervisory authorities are currently using models that estimate a probable rating or a rating downgrade for the individual bank. The models make use of the quarterly call report data and are run every quarter.

The US Federal Reserve developed two variants of its System for Estimating Examination Ratings (SEER) model in 1993, previously called Financial Institutions Monitoring System (FIMS) model. The first variant called the SEER rating model employs a multinomial logistic regression to estimate a bank's probable CAMELS composite rating on the basis of the most recent call report data. Specifically, the model estimates the probability that the bank's next composite CAMELS rating will be each of the five possible ratings (1–5). The SEER rating is the sum of the five rating levels multiplied by their respective probabilities.

The model first determines the historical relationship between call report data and examination ratings by using call report data from two previous quarters and the corresponding latest examination data. The relationship between the dependent (examination rating) and explanatory variables (from call reports) as estimated during this period is then used to estimate events during a subsequent period.

The model provides a statistical relationship between the latest composite CAMELS onsite rating and a list of about 45 financial and non-financial variables. Since the estimation period is not fixed, the variables in the model as well as their coefficients change from quarter to quarter. The variables finally used in the model are selected by the backward regression technique. Those variables that are found to be not statistically significant in predicting the composite CAMELS rating for the current quarter are eliminated from the model. Amongst the variables generally used in the model are past due loans, non-accrual loans, foreclosed real estate loans, tangible capital, net income, investment securities, the Uniform Bank Surveillance Screen (UBSS) asset growth percentile score, UBSS composite percentile score, prior management rating, and prior composite CAMELS rating. The model then combines the weights of the selected variables with the current value of those variables from call reports for each bank to estimate the probable composite CAMELS ratings for the respective institution. If the estimate is significantly different from the most recent onsite examination rating, the bank is singled out for further review.[9] The SEER rating model is now being tested to work as a rating downgrade model to identify only those banks that are at a risk of downgrade.

9 This happens when a bank with a most recent composite CAMELS rating of 1, 2 or 3 receives a rounded SEER rating of 3+, 3+ and 4+, respectively.

The SEER rating model is also used to assist in estimating the bank component of the BOPEC rating.[10] The BOPEC composite rating of a bank holding company is highly correlated with the bank component. The SEER rating of the bank is therefore used as an off-site surveillance rating for bank holding companies. For a single-bank holding company, the SEER rating is the same as the subsidiary bank's rating. For a multi-bank holding company, the SEER rating is calculated as the asset-weighted average of its subsidiary banks' SEER ratings to be used in BOPEC.

The FDIC developed the Statistical CAMELS Off-site Rating (SCOR) model in 1995 to replace the CAEL off-site rating system. SCOR is run every quarter on the basis of call report data, and uses an ordered logit model of CAMELS ratings to estimate likely downgrades of banks with a current composite CAMELS examination rating of 1 and 2. The reasoning is that banks that have received an on-site examination rating of 3, 4 or 5 are already subject to greater supervisory surveillance. It is the currently strong and satisfactory banks that need to be surveyed for a probable downgrade. The model compares one-year prior call report data to the current on-site examination rating. The coefficients of the estimated relationship are used in conjunction with present call report data to estimate future ratings. The assumption is that the relationship as determined between the prior call and current examination rating will continue to hold in the future. Banks at risk of a downgrade are flagged for review.

SCOR uses a step-wise estimation to eliminate variables that are not statistically significant. However, in general the variables used in the model and the coefficients remain stable from year to year. The SCOR variables include equity, loan loss reserves, past due loans 30–89 days, past due loans 90 days and above, non-accrual loans, other real-estate owned, charge-offs, provisions for loan losses, income before taxes and extraordinary charges, volatile liabilities, liquid assets and loans and long-term securities. The flow variables (charge-offs, provisions for loan losses and income before taxes) are measured using four-quarter totals, and stock variables are taken as end of quarter figures as reported in the call report. If the relationship between these variables and examination ratings changes, it is reflected in the model through a change in the coefficients. Many of the variables used in the model are in fact similar to the ones used in the SEER rating model of the Federal Reserve. However, the prior period CAMELS rating is not included as a variable in SCOR, as is done in SEER rating model.

The time horizon for rating estimation under SCOR is four to six months. Estimations have also been tested over a longer horizon of 12–18 months, but the accuracy of the output was found to decline beyond the six-month period.

[10] See Section 3 – Supervisory bank rating systems.

The SCOR output is in the form of a table giving the probability of each of the five ratings becoming the next composite rating of the bank. If the bank is presently rated 1 or 2, the probability of its downgrade will be equal to the sum of the individual probabilities of ratings 3, 4 and 5. The present threshold flags a bank with a higher than 30% downgrade probability for further review. The output also produces a separate SCOR rating on the basis of each of the five ratings multiplied with their respective probabilities and their subsequent summation. In the final analysis, the SCOR output also attempts to highlight specific areas responsible for estimated rating downgrades. This is done by comparing banks at risk of a downgrade with a "Median 2 Bank", which is a typical 2-rated bank. The Median 2 Bank is a statistical construct making use of median financial data for all banks actually rated 2 in on-site examinations over the past year.

As the rating downgrade model estimates downgrades based solely on deterioration in financial ratios it is believed that such models will be more accurate in forecasting rating downgrades during recessions.

The variables used in rating and rating downgrade estimation models and the positive or negative impact on the model output are listed in Annex 2.

(b) Failure or survival prediction models

Models that aim to predict the failure or survival of a banking institution are based on the premise that banking institutions that fail or experience financial distress typically display similar behaviour a few years prior to such an event. These behaviours can be identified through an analysis of their financial condition. The models therefore attempt to identify the correlations and the coefficients of correlations between certain financial or economic ratios and bank failures and distress. Models are estimated on a sample of failed or troubled banks, tested on another hold-out sample of failed or distressed banks for estimation accuracy, and then used out of sample to identify banks whose ratios or indicators most resemble those estimated in the models. To construct such models, it is essential to have historical data of banks that have failed. If there is no history of failures, or if there are very few failures, estimation may be attempted using data of known weak or distressed banks, in which case it is necessary to develop a precise definition of a weak or distressed bank.

The second variant of the US Federal Reserve's SEER model mentioned earlier is the risk rank model, which estimates the probability from 0–100% that a bank will fail (or become "critically undercapitalised")[11] during the subsequent two years. The estimation is based on a bank's financial

[11] Critically undercapitalised is defined as a ratio of tangible equity to average assets of less than 2%.

condition as measured on the basis of the most recent call report data. The risk rank is a single statistic summarising the estimated risk of failure for the respective bank.

The model employs a bivariate probit regression technique to estimate the probability of failure. This means that the dependent variable takes either of the two values, 1 for failure and 0 for survival. The model makes use of the characteristics of bank failures in the United States during the period 1985–91 to provide a statistical relationship between bank failures and financial information. Being based on call report data as the input data, the model is run every quarter.

When the model was initially developed, the estimation period for the model changed every quarter, as it used two prior years as the estimation period to calculate the variable weights. However, as the number of bank failures decreased through the 1990s, a model was developed on the basis of pooled cross-section and time series data for the period 1985–91. The model makes use of 11 explanatory variables, the individual bank values of which are used to calculate risk rank. The model automatically flags banks with a risk rank higher than a predetermined threshold for more intensive review by Federal Reserve Bank analysts.[12]

The output of the model, which was initially a simple listing of the variables that contributed to a bank failing the risk rank criteria, was updated in 1997 to include a detailed "risk profile analysis" which includes a "peer analysis" and a "change analysis" for each individual bank. The former reports information about the risk of a bank relative to its peers and the latter provides information about the factors responsible for the changes in a bank's risk rank over time. The distribution of risk ranks across banks and its average also provides measures of the current level of risk in the banking industry based on financial information reported in the call reports.

At present the OCC does not use any statistical early warning model for supervisory purposes. However, several research efforts have been initiated over the past few years in this field, and some models developed were tested for their forecasting ability. The probability of failure model attempted to predict the probability of a bank failing over a four-year period. The model tried to distinguish high-risk banks from low-risk banks making use of nine explanatory variables, including indicators for state-wide branches and urban headquarters. The model was developed on a pilot basis only, using a sample of de novo banks from 1981–89. The probability of survival model attempted to predict the probability of survival beyond a two-year time horizon. The model made use of five explanatory variables from call report data to distinguish high-risk banks from low-risk banks. It was originally

[12] This happens when a bank with a most recent CAMELS rating of 1, 2 or 3 has a chance of failure higher than 2%, 2% and 3%, respectively as estimated by the model.

developed using data and failure experience from 1986–88, and was subsequently also tested for the period 1989–93. Neither of these models is currently in active use.

The OCC has now launched an initiative designed to use predictive tools more effectively. The initiative has been termed "Project Canary" (an allusion to a canary in a mineshaft whose death warns miners of deadly gases that would otherwise go undetected). The project will comprise early warning models that will enable the supervisor to spot emerging trends in industry risk and project future events accurately.

The Bank Calculator model of the OCC will be a part of Project Canary and is being tested and validated for use shortly. The objective of the Bank Calculator model is to identify for the examination staff rising overall risk of bank failure and particular "banks-at-risk". Banks-at-risk are those banks that may experience a rising probability of failure. The intention is for the model to identify potentially troubled banks before indications of trouble appear in banks' financial statements and before an examiner downgrade. Given these objectives, the model will look at data beyond financial data, will be an absolute rather than a relative risk model, and will mainly be used in the case of small and medium banks. For large banks, the supervisor will look at additional risk assessment methods apart from the model.

The model is estimated using the standard logistic regression method. The dependent variable is the sum of bank failures and troubled bank mergers[13] over the total number of nationally-chartered banks. The independent variables will relate to three main categories of risk:

(i) Bank portfolio risk – this will include variables relating to asset-liability mismatches, illiquidity in funding, troubled loans and prior CAMELS ratings of 3, 4 or 5. The last will serve as a broader measure of bank condition, and ensure that those banks that have already been identified as problem banks by the bank supervisor are also flagged in the model.

(ii) Bank condition risk – this relates to the ability of the bank to withstand shocks and includes measures of profitability and capital.

(iii) Bank environment risk – this relates to the impact of the environment on a bank's working and risk profile. Measures of bank environment risk include the change in the unemployment rate within each bank's market area. The market area is taken as the county where the main office is located for banks with assets under USD 500 million, and the state where the main office is located for banks over USD 500 million in assets. Preliminary testing has shown

[13] Troubled bank mergers have been defined in the model as mergers of banks with capital below 4% or with a profitability measure used by the OCC that is less than 0.5%.

that the level of unemployment in a bank's market area is significant in accounting for bank failure. The model also makes use of some control variables to control for differences in sub-populations of banks or changes in the regulatory regimes in which they operate. These variables relate to bank size over or under USD 500 million in assets, the age of the bank charter, and two variables for regime shifts that have taken place in the United States.

The critical level in the model has been set at 25%; this means that if the model shows that a bank has a failure risk above 25% it will be flagged. The level has been set so that the model accuracy is 50% denoting a calibration that sets Type I error equal to Type II error.

The time horizon for prediction in the model will be two years, and it is expected to run annually. Preliminary testing of the model has shown that it does predict rising risk of failure at least six months before a CAMELS downgrade preceding failure. The model fit is found to improve significantly in moving from a two-year to a maximum of a three-year time horizon, indicating that failure or merger is most likely to occur within three years of bank stress.

The Bank of Italy is developing a duration model to assess not only the likelihood of bank failure over a fixed time horizon but also the timing of the event. The dependent variable in the duration model of Bank of Italy will be measured as the time in months to failure. The model focuses on the conditional probability of bank failure in the next period given that it has survived as long as it has. By contrast, the probit and logit models of the US supervisors discussed earlier focus on the unconditional probability of failure at some unspecified point of time over a time horizon set in the model.

On account of the absence of a sufficiently wide data set for failed institutions in Italy, the definition of failure has been modulated to include distressed banks or banks that were liquidated or taken over while in distress in the sample for estimating the model. To test the performance of the model a recent sample of troubled banks was taken to be those banks that were assigned an off-site (i.e. PATROL) rating of 3 and above. A number of variables are currently being tested for use as explanatory variables in the model.

The variables used in failure/survival prediction models along with the estimated signs of the coefficients are provided in Annex 3.

(c) Expected loss models

Countries that do not have a history of bank failures or have had only infrequent failures may find it difficult to estimate a failure or survival prediction model, as there would not be enough statistical evidence to link financial variables to failure. In such a situation alternatives include having a modulated definition of failure, as is done by Bank of Italy in its early warning model (see above), or trying to predict the future solvency of a banking institution by estimating potential future losses, as is done by the French Banking Commission.

The French Banking Commission's Support System for Banking Analysis (SAABA) model has been in use since 1997. Though it is a statistical model, it also makes ample use of qualitative assessments to fine-tune the quantitative analysis. The quantitative aspect of the model is based on the premise that credit risk is the major risk that banks face, and the system software is designed to undertake detailed credit portfolio analysis of each banking institution to work out its future solvency. The final diagnosis includes qualitative assessments relating to ownership and shareholder quality, as well as management and internal controls. The SAABA model is run every six months.

The input data and information come from the Banking Commission's own databases, the Bank of France database and also external sources. The Banking Commission sources include accounting and regulatory reporting data, surveys on property risk, database relating to defaults of firms maintained within SAABA, information from the ORAP off-site rating, inspection information, shareholders commitment data, data on consolidations and country risks. Bank of France data include the rating for creditworthiness of corporates and risk analysis scores for corporates. External sources include credit ratings of banks by various credit rating agencies. By drawing on these databases, the SAABA software aims to take into account various facets of banking risk and capture vulnerability factors as comprehensively as possible.

The methodology for the quantitative dimension of the model involves adjusting all outstanding individual and corporate loans of a banking institution with a potential future loss amount. The potential loss amount is based on the default probability worked out in the case of each individual credit on the basis of data and information available as mentioned above. Individual potential losses are summed to arrive at a total for the entire credit portfolio over a three-year period. This total potential loss figure is then adjusted against the current level of reserves. The unadjusted balance represents the potential future loss, which is deducted from the current level of the bank's own funds. If after this adjustment the own funds continue to be higher than the minimum requirement of 8%, the bank is expected to remain solvent over the next three years. If, however, the own funds fall below the 8% requirement after the quantitative analysis, the bank's future solvency is questionable.

SAABA complements the quantitative diagnosis with two other diagnoses. One of these relates to shareholder quality and consists of an assessment of equity ownership, consolidated group to which the bank belongs and the ability and willingness of shareholders to support the banking institution. The other diagnosis relates to management, internal controls and liquidity on the basis of the on-site examination report and ORAP rating, asset liability management, and market feedback on the institution.

The output includes a synthetic diagnosis as well as a detailed analysis of the banking institution. The synthetic diagnosis classifies an institution in one of the following five categories:

(i) weak without qualification – an institution having an anticipated solvency ratio of less than 8% with no certain support from shareholders

(ii) weak – anticipated solvency ratio of more than 8% but no shareholder support

(iii) fragile – anticipated solvency ratio of less than 8% but strong shareholder support

(iv) normal under reserves – anticipated solvency ratio of less than 8% but belongs to a strong French banking group whose group solvency ratio is more than 8%

(v) normal – anticipated solvency ratio of more than 8% and strong shareholder support.

The model automatically releases a diagnosis list of all credit institutions. On request, user access to detailed analysis of a credit institution is also available. The SAABA outputs assist in planning for on-site supervision as well as for making aggregations, conducting thematic analysis relating to exposure of the main banking groups to small and medium firm risk and running a simulation exercise to judge the consequences of a sector-related crisis on the banking system.

(d) Other models

The FDIC's Growth Monitoring System (GMS*)* developed in the mid-1980s is a simple early warning model essentially designed to detect what is deemed to be the initial stage in the life cycle of failing banks – the rapid growth stage. The premise of the model is that rapid growth in total assets or loans could signal risky behaviour by banks of which supervisors should be aware. Growth-related risk can arise in two areas – loans and bank management. There may be increased loan concentrations in risky areas and there may be management lapses such as lowered underwriting standards, increased reliance upon volatile funding or a general weakening of internal controls in order to facilitate rapid growth. The model however makes a distinction between internal and external (i.e. merger-related) growth to account for the fact that the former is potentially riskier.

The model is run every quarter using call report data as the input. It is based upon the levels and quarterly trends of six summary measures, which are reflected in four ratios and five growth rates as the independent variables. The ratios are measured on a quarter-to-quarter basis, but the growth rates are measured on a year-to-year basis to eliminate seasonality in the data. The ratios and growth rates used in the model are listed in Annex 4.

The four ratios are compared relative to the peer group to which the bank belongs and the five growth rates are compared relative to all the US banks taken as a peer group.[14] The comparison involves

[14] Originally peer groups in GMS were set according to asset size and geographical regions. This has now been modified to include peer groups based on asset size only. So far, five peer groups based on asset size have been constructed. FDIC is

deducting the peer group growth rate or ratio from that of the bank. For instance, if a bank's asset growth rate is 50% and its peer group's growth rate is 4%, the bank has grown 46% more than its peers.[15] This exercise is done for each of the independent variables. The results are subsequently weighted in a two-step process and the weighted results are summed to give a composite GMS score.

The composite GMS score is evaluated separately for two groups of banks. The first group is composed of banks whose quarterly asset and loan growth rates are 5% or more (high-growth banks), the second of banks with quarterly asset and loan growth under 5% (low-growth banks). For all high-growth banks, composite GMS score percentile rankings are computed. Banks in the highest composite GMS score percentile (currently the 95–99th percentiles) are flagged for further off-site review. Supervisors may also review banks below the 95th percentile, particularly those with poor CAMELS ratings.

A concentration variable has now been included in the model. The variable measures the effect of a bank moving into or expanding in a line of business. It first measures the individual changes in concentrations in various loan categories. The positive changes are taken into account while the negative changes are set at zero. The rationale is that the supervisor is concerned with the risks that a bank may face by moving into or expanding a line of business, particularly where it has limited experience, as opposed to exiting from a line of business. The positive changes or growth numbers are then weighted by the national average charge-off rates for those types of loans, as they are taken to be most reflective of the risks in different types of loans.

The model will also be tested with further changes that may include elimination of the level of equity ratio, and the growth rate of loans and long-term securities. Instead, the model may include loan-to-asset ratios. Additionally, inclusion of a minimum loan-to-asset ratio test of 25% in the model is being considered. This would mean that the model would ignore the loan growth or change in concentration of a bank that has a loan-to-asset ratio of less than 25%. The use of net interest margin in the model is also being evaluated. Changes in the margin may well indicate that a bank is acting aggressively, which may need further exploration.

The Trigger Ratio Adjustment Mechanism (TRAM) early warning model developed by the Bank of England in 1995 (but not implemented) was designed to make assessments of a banking institution based on a mix of statistical methods and subjective judgements. The assessments relate to three major

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now actively considering using business lines like credit cards, agriculture lending, commercial lending, home mortgages, etc. as peer groups in the system.

15 Initially, the model used percentile rankings for each of the independent variables, which were subsequently weighted in a two-step process, and then summed to arrive at a GMS score. Percentile rankings, however, tend to lump together all tail data, giving a skewed interpretation of differences in growth rates. A bank that grows at 60% may be in the 95th percentile, 20% growth may be in the 85th percentile and 10% growth may be in the 45th percentile. The difference between 60% and 20% growth is only 10 percentile whereas the difference between 20% and 10% is 40 percentile.

categories of the functioning of a banking institution: the profit stream, the risk profile and control and structure. All three categories are considered equally important and are weighted equally in the model. However, individual components within each category are assigned different weights based on their significance and predictive power. Assessments of individual components are done on the basis of data tests based on artificial intelligence. Where data are unavailable or inappropriate, e.g. in the control and structure category, score cards based on supervisory judgement of the bank's performance in relation to specified objective criteria are used. The result of each data test and scorecard is subjected to transformation by the software that maps them on to TRAM scores of 1 (best) to 10 (worst). The overall TRAM score results from the mapped TRAM score multiplied by the weight assigned to the assessment component. High scores in individual components as well as the overall TRAM category would signal potential problems in the banking institution.

Issues

Statistical early warning models are based on rigorous quantitative analysis. As such, the impact of qualitative factors such as management quality, internal control and other bank-specific factors like credit culture, underwriting standards, is not typically represented in the models.[16] It is widely acknowledged that these qualitative factors, particularly the efficiency or inefficiency of management, can also be significant causes of bank failure. However, few models attempt to quantify management quality or incorporate realistic surrogates for management performance. The models are also not designed to capture the risk of failure on account of other non-financial factors like fraud or financial misconduct.

The low number of failures in G10 countries in the past few years has made it difficult to estimate and test failure models in some countries, or to revalidate models originally designed to capture the economic conditions and banking industry structure of earlier periods of distress. Many of the existing models have been developed and put to use in relatively favourable economic conditions. The models have yet to undergo the test of a full economic cycle to enhance their reliability. Another related difficulty faced by some supervisors is the small number of institutions in the banking sector. To estimate models it is useful to have reasonable sample sizes, which is not the case in some of the G10 countries.

In statistical models it is important to correctly identify causal variables and relationships to ensure that important variables are not overlooked and spurious ones are not included. It is therefore

[16] The SEER rating model of the Federal Reserve does incorporate a proxy for management, by using the Management component rating from CAMELS assigned during the previous on-site examination, while estimating the probable rating in the model. The SAABA model of the French Banking Commission complements its quantitative analysis with a separate qualitative assessment.

important to distinguish coincidences from true causal relationships. The variables included need to be based on rigorous statistical procedures and economic reasoning. This is particularly relevant in a model where the estimation period is fixed so that the independent variables once selected remain fixed. The selection of the variables should be based on rigorous statistical testing for their explanatory and predictive power. In a dynamic model where the estimation period varies, the explanatory variables should be regularly tested for their significance, and eliminated if the results show a decrease in their significance as explanatory and predictive variables.

As with the choice of variables, weights assigned need to be based on the significance and the predictive power of individual explanatory variables and determined on the basis of rigorous testing. Further it is essential that the weights assigned to explanatory variables be continuously evaluated for output accuracy.

Another important issue with respect to early warning models relates to the methodology used and the corresponding statistical requirements for model estimation. Ideally, supervisors would like to develop models that can predict future failure. However, such models are difficult to estimate unless there are extensive historical data on bank failures, which is not the case in many of the G10 countries covered here. If there is no history, or only a limited history of failures, supervisors may attempt to construct models by using data for known weak or distressed banks. If the model has to predict the extent of the threat to insolvency due to potential losses, it is useful to have data on individual loans and various risks associated with the expected returns.

The availability of extensive, clean and reliable input data is a key ingredient in the formulation of early warning models. The predicted output of the model will only be as good as the input data. This concerns not only the variety and integrity of the data reported by banks under regulatory reporting but also the availability and integrity of any other database that may be used in the model. Supervisors already using early warning models are constantly working towards improving the nature, variety and integrity of the input data. One US supervisory authority is now exploring the possibility of using data obtained from private sector credit bureaus in its early warning models.

Time horizons currently used by supervisory authorities in statistical models are typically in the range of a few months to three years. Models used to estimate ratings or rating downgrades tend to have a shorter time horizon than those trying to predict failure or compute expected losses. The time horizon set for the model within the medium or long term, should be one over which the model is tested and found to predict most accurately.

Inherent to all statistical models is the trade-off between two types of errors. A Type I error occurs when a model incorrectly identifies a weak bank as a strong bank, and a Type II error occurs when a strong bank is mistakenly identified as a weak bank or a bank likely to fail. For a supervisor, a Type I error is potentially more serious than a Type II error. This is because a weak bank that may escape supervision entails a higher risk in terms of depositor value, risk to other institutions and resolution cost to the supervisor than a strong bank being subject to additional surveillance or examination. Supervisory authorities aim at minimising the Type I error rate, and models can be calibrated to carry a low Type I error. However, this also means that the model will have a high Type II error and will incorrectly classify a number of strong banks as weak. The level of the actual trade-off will depend upon the model accuracy and the extent to which the supervisory authority is willing and able to undertake increased examination and surveillance of strong banks to identify a greater proportion of weak banks. Since statistical models are new and their output is generally supplemented with those from other systems in identifying problem banks, supervisory authorities continue to use and fine-tune the models despite the outcomes of the error rate trade-offs.

The early warning models in use are subject to some form of backtesting and validation studies. The Federal Reserve reportedly undertakes an annual validation study for the SEER rating and risk rank models, which compares the predictions made by the models with the actual examination rating or event. The composite rating estimated by the SEER rating model is compared with the actual rating assigned by the examiner to determine that model's performance. To evaluate the predictive ability of the SEER risk rank model, the number of estimated failures (survivors) is compared with the number of actual failures (survivors) and the Type I and Type II error rates are computed. Similarly, the French Banking Commission reports that periodic backtesting is carried out to ascertain whether the model correctly identifies banks that are likely to run into serious problems in the future. To test the efficacy of its GMS model, the FDIC compares GMS composite scores with future bank failure rates. The analysis shows that banks in the lowest GMS score decile usually fail at the highest rate during the two years immediately after the scores were measured and those in the highest GMS decile fail at the highest rate between three and five years after the scores are assigned.

Statistical models currently in use are mainly unconditional models. The models predict that a bank is likely to fail in the future or that its condition will deteriorate given the current value of the independent variables. They do not condition the forecast on assumptions about the future path of any of the variables included in the model. Some supervisory authorities are now attempting to develop models based on forecasts of individual bank variables and the resultant failure or survival probability.

While some of the early warning models have achieved satisfactory results, it has been in limited contexts. The challenge of accurately predicting the probability of a rating downgrade, probability of failure or survival, expected losses or insolvency, over a wide range of institutions and time periods has proven to be difficult. Since early warning models are a relatively new development, it is not surprising that further work is being carried out to improve their performance. Possible future lines of action include:

- Developing models using market-based indicators such as spreads on subordinated debt. These can be particularly relevant for large banks as in their case the usefulness of the various systems mentioned earlier is limited. Studies have been undertaken by the US Federal Reserve to ascertain how bond market information can be used to infer bank risk.[17] The study has found that appropriately adjusted subordinated bond yields may provide a good estimate of changes in the market assessment of a bank's default risk. Subordinated debt holders' incentive to monitor bank risk arises from the fact that the debt ranks lowest in priority among bank liabilities. These instruments carry the perception that in the event of bank failure the government may not bail out subordinated debt holders and because, unlike shareholders, they do not benefit from upward potential of increasing risk. However, in using the information from subordinated debt spreads in supervisory risk assessment and early warning systems, factors like prevailing interest rates for debt with similar maturity, instrument characteristics, liquidity of the issue and bank default risk need to be taken into account. None of the models currently in use consider subordinated debt spreads as an explanatory variable. However, as the banking sector moves towards more market discipline, and as markets become more efficient and informed, there is likely to be greater use of market information in supervisory risk assessment and early warning systems.

- Use of economic data in early warning models. Preliminary research has shown that the inclusion of local economic data in early warning models improves their accuracy only marginally. A study conducted by the FDIC shows that in the case of small regional or local banks, state-level economic data does impact performance. Hence regional economic variables, like state-level personal income growth rates and unemployment rates, do add limited value to long-term forecasts of rating downgrades. However, given the growing trend of consolidation and geographical diversification of the banking industry, national and international economic conditions assume greater relevance in their impact on bank performance. As national-level data become available only with a time lag, their use in statistical models may lose their relevance and purpose. Moreover, the fact that bank-specific factors like management or internal controls may cause banks in similar economic conditions to perform very differently can also affect the utility of economic data in statistical models. Further research is being undertaken in this area.

- Revisiting the nature and structure of regulatory reporting so as to make it more representative of the business and risk profile of the banking institution. This would help in

[17] Board of Governors of the Federal Reserve System Staff Study 172, December 1999 - *Using Subordinated Debt as an Instrument of Market Discipline.*

making the models more accurate, as well as more applicable than at present to big banks undertaking diversified business activities.

- Increasing the use of models for stress testing and scenario analysis.
- Improving and simplifying the output of the models so that it can be put to more effective use by examiners and other users.

Conclusions

Overall problems in the banking sector can be identified through macro banking data. However, such aggregated data may tend to conceal serious problems within individual banking institutions. As the stability of the banking system also depends on the safety and soundness of individual banks, it is useful to have specific systems in place to effectively monitor the risk profile and financial condition of each institution. There is now a distinct move in this direction as supervisors aim to have a more structured approach to ongoing supervision with a greater emphasis on formal risk assessment and risk detection methods. There is also an increased realisation of the worth of qualitative factors in detecting and assessing risk. In addition, an increased effort is under way to combine the potential of artificial intelligence of software with expert human judgement in order to produce accurate risk assessments of banking institutions.

Supervisory authorities currently using the risk assessment and early warning systems covered by this paper find them useful in their ongoing risk-focused banking supervision process. Supervisory authorities that carry out periodic on-site examinations use the systems to assess the financial condition and risk profile of banks between examinations, to identify institutions that need to be examined ahead of schedule as well as areas within institutions that need to be specifically examined. In countries where on-site examinations are not specifically mandated, or where the frequency of on-site examinations may be restricted on account of supervisory resource constraints, such systems constitute the primary tool for identifying institutions that need to be subjected to on-site examination in the first place.

Supervisors also acknowledge the fact that most of the risk assessment and early warning models, with perhaps the exception of comprehensive bank risk assessment systems, work best in the case of small and average-sized banks that essentially engage in traditional banking activities. Most systems and models may not be very effective in accurately assessing the risk profile and financial condition of large domestic or internationally active banks, of banks doing specialised business, or of banks engaged in non-traditional activities and new business areas. One of the reasons is that most of the systems rely heavily on regulatory reporting data, which itself does not necessarily reflect fully and adequately the diverse nature of activities undertaken and the risks assumed by these large or specialised banks. For such institutions, supervisors tend to use a variety of methods for risk assessment and early warning of potential problems. These include: relying to a certain extent on the bank’s internal models for risk assessment; constituting dedicated supervisory teams which include experts for specific types of risk analysis; obtaining regular internal management reports; conducting meetings with senior bank management on an ongoing basis; obtaining information on business lines and market evaluations from third parties such as rating agencies; and reviewing banking developments with other supervisors.

Not surprisingly, this study of various risk assessment and early warning systems reveals that leading indicators of bank problems are the various asset quality indicators. Liquidity, profitability and solvency constitute either concurrent or lagging indicators of bank distress. This reinforces the fact that the first signs of bank financial problems can often be detected in various asset quality indicators, in particular the past due indicators. These indicators are generally reflective of the prevailing economic conditions and many supervisory authorities require them to be reported non-discretionally. An overview of the various indicators used in supervisory risk assessment and early warning systems is provided in Annex 5. As is evident from the large number of asset quality indicators used in early warning models, these indicators gain in importance when assessment is done over a medium- to long-term horizon. In the short term, profitability, liquidity and solvency indicators provide useful information on banks’ financial condition.

There is as yet no automatic and direct link in most of the supervisory risk assessment and early warning systems with formal prompt corrective action frameworks. Institutions identified as potentially risky by the systems are typically subjected to greater supervisory surveillance and on-site examination before enforcement of formal actions is initiated. However, as the reliability of the systems' output increases, it is possible that a direct link between the output and formal corrective action will be established.

Supervisory authorities are already exploring the use of additional data sources apart from the regulatory reporting data in the systems. Some of the off-site rating systems, financial ratio and peer group analysis systems, and models covered in this study attempt to include data and information from sources other than regulatory reporting and proprietary supervisory information in making assessments of banking institutions. Continuous attention is also being focused on the timeliness, integrity and variety of regulatory reporting data, which are a vital input in all the systems.

Formal supervisory risk assessment and early warning systems developed and put to use in the last few years have been of assistance to the supervisors. As the systems are relatively new and in the process of stabilisation, they will require further adjustment, refinement, modification and validation to gain further supervisory confidence in the reliability of their performance. There is no doubt, however, that in objective, approach, spirit and content the new systems may prove to be not only an improvement over the earlier systems but also more consistent with the changing environment of the financial sector. The systems can also be very useful and significant complements to the supervisory review process (Pillar 2) as contemplated in the proposed revision of the 1988 Basel Capital Accord. Such systems are likely to be increasingly developed and adopted as part of a comprehensive and restructured approach to risk-focused supervision, in G10 as well as non-G10 and emerging market countries.

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Annex 1

Bank Rating System: CAMELS

The CAMELS rating system is subjective. Benchmarks for each component are provided, but they are guidelines only, and present essential foundations upon which the composite rating is based. They do not eliminate consideration of other pertinent factors by the examiner. The uniform rating system provides the groundwork for necessary supervisory response and helps institutions supervised by all three US supervisors to be reasonably compared and evaluated.

CAMELS components

Capital adequacy

- Size of the bank
- Volume of inferior quality assets
- Bank's growth experience, plans and prospects
- Quality of capital
- Retained earnings
- Access to capital markets
- Non-ledger assets and sound values not shown on books (real property at nominal values, charge-offs with firm recovery values, tax adjustments)

Asset quality

- Volume of classifications
- Special mention loans – ratios and trends
- Level, trend and comparison of non-accrual and renegotiated loans
- Volume of concentrations
- Volume and character of insider transactions

Management factors

- Technical competence, leadership etc of middle and senior management
- Compliance with banking laws and regulations
- Adequacy and compliance with internal policies

- Tendencies towards self-dealing
- Ability to plan and respond to changing circumstances
- Demonstrated willingness to serve the legitimate credit needs of the community
- Adequacy of directors
- Existence and adequacy of qualified staff and programmes

Earnings

- Return on assets compared to peer group averages and bank's own trends
- Material components and income and expenses – compare to peers and bank's own trends
- Adequacy of provisions for loan losses
- Quality of earnings
- Dividend payout ratio in relation to the adequacy of bank capital

Liquidity

- Adequacy of liquidity sources compared to present and future needs
- Availability of assets readily convertible to cash without undue loss
- Access to money markets
- Level of diversification of funding sources (on- and off-balance sheet)
- Degree of reliance on short-term volatile sources of funds
- Trend and stability of deposits
- Ability to securitise and sell certain pools of assets
- Management competence to identify, measure, monitor and control liquidity position

Sensitivity to market risk

- Sensitivity of the financial institution's net earnings or the economic value of its capital to changes in interest rates under various scenarios and stress environments
- Volume, composition and volatility of any foreign exchange or other trading positions taken by the financial institution
- Actual or potential volatility of earnings or capital because of any changes in market valuation of trading portfolios or financial instruments
- Ability of management to identify, measure, monitor and control interest rate risk as well as price and foreign exchange risk where applicable and material to an institution

CAMELS component ratings

Rating Scale / Component Category	1 strong	2 satisfactory	3 fair	4 marginal	5 unsatisfactory
Capital					
Assets					
Management					
Earnings					
Liquidity					
Sensitivity to market risk					

Composite CAMELS and their interpretation

Rating scale	Rating range	Rating analysis	Rating analysis interpretation
1	1.0-1.4	Strong	Sound in every respect, no supervisory responses required
2	1.6-2.4	Satisfactory	Fundamentally sound with modest correctable weakness, supervisory response limited
3	2.6-3.4	Fair (watch category)	Combination of weaknesses if not redirected will become severe. Watch category. Requires more than normal supervision
4	3.6-4.4	Marginal (some risk of failure)	Immoderate weakness unless properly addressed could impair future viability of the bank. Needs close supervision
5	4.6-5.0	Unsatisfactory (high degree of failure evident)	High risk of failure in the near term. Under constant supervision/cease and desist order

Annex 2

Indicators used in rating models

SEER rating model, US Fed Reserve		SCOR downgrade model, US FDIC	
Variables	**Relationship with risk rating**	**Variables**	**Relationship with risk of downgrade**
Asset quality		**Asset quality**	
Loans past due (30-89 days)	+	Loans Past due (30-89 days)	+
Loans past due (90 days plus)	+	Loans past due (90 days plus)	+
Foreclosed real estate loans	+	Non-accrual loans	+
Non-accrual loans	+	Other real estate loans (foreclosed loans)	+
Earnings		Loan loss reserve	–
Net income	–	Gross charge-offs	+
Liquidity		Provision for loan losses	+
Investment securities	–	**Earnings**	
Capital		Income before taxes and extraordinary provisions	–
Total net worth	–	**Liquidity**	
Other		Volatile liabilities	+
Uniform Bank Surveillance Screen (UBSS) asset growth percentile score	+	Liquid assets	–
UBSS composite percentile score	+	Loans and long-term securities	–
Prior Management rating	+	**Capital**	
Prior composite CAMELS rating	+	Total equity capital	–

+ means the higher the value of the variable, the higher the risk rating or risk of downgrade

– means the higher the value of the variable, the lower the risk rating or risk of downgrade

Annex 3

Indicators used in failure/survival prediction models

SEER risk rank model, US Fed Reserve		Bank Calculator model OCC, US	
Independent variables	**Estimated sign of co-efficient**	**Independent variables**	**Estimated sign of coefficient**
Asset Quality		**Bank portfolio risk**	
Commercial and industrial loans	+	90 days past due loans + non-accrual loans + other real estate owned to total assets	+
Loans past due (30-89 days)	+	Illiquidity in funding (dummy variable to flag banks with more than 15% of liabilities represented by large-denomination CDs plus brokered deposits)	+
Loans past due (90 days plus)	+	CAMELS rating 3,4,5 (problem banks)	+
Non-accrual loans	+	**Bank condition risk**	
Residential real estate loans	–	Earnings before interest and taxes/total assets Divided by Interest on liabilities/total liabilities	–
Other real estate owned (OREO)	+	Capital to assets ratio	–
Asset size	–	**Bank environment risk**	
Earnings		Two year change in unemployment rate in the bank's market area	+
Return on average assets	–	**Control variables (to adjust for differences in banks)**	
Liquidity		Bank size (>< USD 500m assets)	+ or –
Book value of securities	–	Age of bank charter (dummy for charter between 3-5 years old)	
Time deposits greater than USD 100m	+	Regime shift 1 (=1 after 1989 when Financial Institutions Reform, Recovery and Enforcement Act – FIRREA - was introduced)	
Capital Total net worth (equity capital)	–	Regime shift 2 (=1 after 1992 when Federal Deposit Insurance Corporation Improvement Act – FDICIA - was introduced)	

+ indicates increased risk

– indicates lower risk

Annex 4

Variables used in the Growth Monitoring System of the FDIC, US

	Growth rates
1.	Growth rate of total assets
2.	Growth rate in loans and leases
3.	Growth rate of loans and leases plus securities > = 5 years
4.	Growth rate of volatile liabilities
5.	Growth rate of equity capital
	Ratios
6.	Ratio of loans and leases plus securities > = 5 years to total assets
7.	Ratio of volatile liabilities to assets
8.	Ratio of equity capital to assets
9.	Assets per employee

Annex 5

Indicator/risk categories and ratios used in supervisory risk assessment and early warning systems

(i) Supervisory bank rating systems

System/ Country	Indicator categories and ratios used	Asset quality	Solvency	Profitability	Liquidity	Market risk	Management and control	Economic	Others
CAMELS (US)	6	1	1	1	1	1	1	–	–
CAEL (US)	4	5	5	4	5	–	–	–	–
PATROL (IT)	5	1	1	1	1	–	1	–	–
ORAP (FR)	6	4	2	3	1	1	3	–	–

(ii) Financial ratio and peer group analysis systems

System/ country	Ratios used	Asset quality	Solvency	Profitability	Liquidity	Market risk	Management and control	Economic	Others
Bank Monitoring Screens (US)	39 financial +35 capital market	21	5	5	8	_	_	_	35[a]
BAKIS (DE)	47	18	1	10	2	16	–	–	–
Observation system (NL)	53	12	5	13	2	_	_	6[b]	15[c]

[a] Capital market monitoring ratios relating to trading activity.

[b] Macroeconomic indicators – GDP growth, growth in industrial production, unemployment rate, euro/dollar exchange rate, bankruptcies in the past 12 months, spread of yield on 10 year government bonds over 3 month Euribor.

(iii) Comprehensive bank risk assessment systems

System/ country	Risk categories used	Asset quality	Solvency	Profitability	Liquidity	Market risk	Management and control	Economic	Others
RAST (NL)	13	1	–	–	1	3	3	–	5[d]
RATE (UK)	9	1	1	1	1	1	3	–	1[e]

(iv) Statistical models (failure/survival/fragility)

System/ country	Indicators used	Asset quality	Solvency	Profitability	Liquidity	Market risk	Management and control	Economic	Others
SAABA (FR)	5 (indicator categories)	1	1	1	1	_	1	_	_
SEER (Fed, US)	11 (ratios)	7	1	1	2	_	_	_	_
GMS (FDIC, US)	9 (ratios/rates)	6	2	_	1	_	_	_	_
Bank Calculator (OCC, US)	10 (indicators)	1	1	1	1	_	_	1[f]	5[g]

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[c] Capital market monitoring ratios, external ratings, market share.

[d] Operational, IT, strategic, legal and reputational risks.

[e] Business risk – business environment analysis in the context of bank's overall business.

[f] County/state unemployment rate – two-year change.

[g] Age of bank charter, prior CAMELS rating 3,4 or 5, bank size and two indicators for regulatory regime shifts.

(v) Statistical models (rating/rating downgrade estimation)

System/ country	Indicators used	Asset quality	Solvency	Profitability	Liquidity	Market risk	Management and control	Economic	Others
SEER rating (Fed, US)	11	4	1	1	1	–	1[h]	–	3[i]
SCOR rating downgrade (FDIC, US)	12	7	1	1	3	–	–	–	–

h Prior Management rating.

i Uniform Bank Surveillance Screen (UBSS) asset growth percentile score, UBSS composite percentile score, prior composite CAMELS rating.