NONCONFIDENTIAL // EXTERNAL

CAMELS ratings are supposed to provide an indication of the financial condition of a bank. They should be systematically calculated and periodically validated.

One validation procedure is to estimate the likelihood of failure conditional upon a CAMELS rating and future economic conditions. Both the FED and FDIC can do so. The CAMELS ratings ought to be a significant determinant of the probability of failure. To expand on this idea see the attached chapter that appears in *The Most Important Concepts in Finance* (2018) Edited by Benton Gup. (
https ://www. e-elgar .com/shop/the-most-important-concepts-in-finance.)

Although they can provide useful scoring models, they can become more useful in quantifying risk. To do so, CAMELS must be linked to an estimated probability of failure. CAMELS can also be incorporated with stress testing models used to project key financial soundness indicators. Such financial soundness indicators can be used to construct future CAMELS under stress and provide estimates of how the probability of failure may change under stressful conditions.

These conclusions are derived from numerous IMF missions to different countries where IMF technical experts worked with regulators to develop early warning systems. By incorporating qualitative on-site examiner assessments into the CAMELS ratings, more useful early warning systems can be developed.

Tom Lutton

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Tom and Beth Lutton

10. Risk and the probability of insolvency: a regulatory perspective

Betsy Brown Faulk, Walter H. Faulk, and Thomas Lutton

Few concepts in finance and regulation have received more attention than risk: how to define it, estimate it, monitor it, and ultimately manage it. Risk assessment and monitoring requires estimation of the probability of incurring future losses, the magnitude of such losses, and who bears the losses. Regulators charged with monitoring risks taken by banks have increasingly replaced compliance-based banking regulations with risk-based supervision (RBS) since the mid-1990s.[1] In its more sophisticated forms, RBS recognizes the importance of monitoring risks as a forward-looking process that exists in every phase of regulation from licensing through to bank resolution.[2] Estimating likelihood of incurring losses and the size of the losses become essential components of risk monitoring.

As commonly practiced, however, RBS has failed to keep up with advances in risk analytics that appear in the financial and economics literature. A gap has developed between risk assessments made by banks and those made by regulators. Banks actually estimate and quantify risk to themselves. Risk-based supervision does not require regulators to actually estimate and quantify risks to banks, their counterparties, and society at large. Many RBS regulators make no attempt to estimate probability of future losses or incorporate probability into risk assessments. The “risk” in RBS takes on a different and more qualitative meaning than probability defined in a statistical sense.

Risk-based supervision regulators in many countries have been content to leave risk undefined and to treat it in a qualitative fashion. Examination manuals guide examiners to use subjective risk assessments such as “high”, “medium”, and “low” risk. On-site risk monitoring frequently relies on heat maps that do not assess risk as much as they assess how banks assess risk. Such surveillance tools limit the ability of RBS to determine both the direction and magnitude of risk in an objective, systematic, and consistent fashion.[3] Learning from risk assessment mistakes in bank risk monitoring becomes almost impossible when the assessments are qualitative, changing from period to period. Scoring models such as CAMELS are seldom subjected to validation tests.

By treating risk in a qualitative fashion, regulators have sidestepped an important safety and soundness risk metric, that is, the conditional probability of a bank's insolvency. Banks themselves have no incentive to provide such estimates to their shareholders, and few regulators require such estimates.

This chapter suggests that analytical advances and information technology have made possible the explicit estimation and quantification of the probability of insolvency by both banks and regulators. This is not meant to suggest that such estimation and quantification is easy and without challenge, but regulators who adopt RBS should be able to define, estimate, and monitor risks in the context of the probability of bank insolvencies.

RISK ESTIMATION AND MONITORING

The estimation and monitoring of risk has received considerable attention in the economics and finance literature since the publication of Frank Knight's *Risk, Uncertainty, and Profit* in 1921.[4] Knight distinguished risk from uncertainty by suggesting that risk could be estimated and quantified through the use of conditional probability distributions associated with future losses, whereas uncertainty could not be estimated. A rich literature has developed over the past century on how to estimate probability and incorporate it into an objective assessment of risk.[5]

Banks routinely quantify risk in their portfolio and pricing decisions, and attempt to exploit the latest information on risk estimation as part of their risk management strategies. They produce business plans which are provided to shareholders and regulators alike, develop risk management and hedging strategies, and price financial products based upon their ability to quantify risk. Competition compels them to do so and risk premia associated with financial instruments are often whittled down to a few basis points, underscoring the importance banks place on objective risk assessments. A question for RBS that looms large almost a century after Knight's treatise is "Should bank regulators be expected to estimate risk as part of their risk monitoring?"

Although the precise definition and estimation of risk in the context of probability remain contentious, there is general agreement that risk estimation and monitoring should consist of two key components: direction and magnitude.

The first is that a risk should reflect the likelihood, probability, or potential of future losses. As probability of incurring future losses for a bank increases (decreases), from one period to the next, the direction of its risk becomes obvious, viz. risk increases (decreases). The second concerns the magnitude of future losses, that is, the extent of the losses that could occur if the risk materializes as a loss.

Neither direction nor magnitude of risk alone provide a sufficient risk metric, but together they can be combined to provide a critical estimates of risk exposure including "expected losses" and "unexpected losses." The latter is used to calculate "economic capital" which has received considerable attention in the capital adequacy literature and in the Basel Accords.[6]

Let's take a closer look at risk and future losses. Statistics, finance, and economics approach future loss as a conditional random variable which may be characterized using a probability distribution. Future losses of course are unknown but probability distributions provide a vehicle to estimate the probability of future losses and estimate risk. "Expected losses," the mean or first moment of such distributions, provide the best guess for future losses given assumptions about future macroeconomic conditions. Variances and higher moments of such future losses affect estimates of the likelihood that losses might exceed extreme amounts and threaten solvency.

The probability of losses sufficiently large to compromise the solvency of a bank provide a valuable safety and soundness metric and should serve as the basis for risk discussions between the banks and examiners. However, the losses associated with insolvency are not limited to just the losses incurred by bank owners (shareholders) and managers. An insolvency may impose losses on others including uninsured creditors, counterparties, and in the case of systemically important banks, and society as a whole. Such losses are not the responsibility of the bank, but are the responsibility of the regulator and must be factored into risk assessments and risk monitoring. Risk-based supervision assessment of risk is not limited to the risk borne by shareholders.

Banks define, estimate, monitor, and manage risks in terms of potential future losses that would be borne by the banks, their owners, and managers. The relationship between risk and probability of future losses appears in a variety of internal risk models used by banks. Banks employ value-at-risk (VaR), distance to default models, Black-Scholes-Merton models, limited dependent variable econometrics models, stochastic asset and liability models, and a variety of stress tests to estimate and monitor risk. Advances in information technology, data management, and risk related software during the 1980s and early 1990s permits banks to routinely incorporate such tools as part of normal course of risk management. New models and risk assessment techniques continue to emerge. Commercial rating agencies since the 2007 financial crisis have begun to offer estimates of probabilities of default for individual banks as commercial products.[7]

It is relatively simple for a bank to assess the losses associated with an insolvency. Assessing impact is a structured exercise that answers the question: if a bank insolvency were to happen, what losses would occur and who would bear them? Stockholders lose their investment; managers become unemployed. Regulators must determine how to address the insolvency through mergers or liquidations, although regulators now require banks to construct "living wills" to develop a plan for insolvency. Regulators, however, must consider not only with potential future losses to the banks, but also losses to bank counterparties and society as a whole. Such losses can be particularly challenging to estimate if the data on cash flows is not readily available.

Even so common factor exists between the bank and regulator, apart from the impact assessment, that is, the probability of insolvency. The perspective on who bears the losses may differ, but the probability of insolvency becomes a critical component in determining risk exposure.

This emphasis on risk assessment within banks, ultimately required bank supervision to move from backward-looking compliance-based bank supervision to a more forward-looking RBS in the mid-1990s. Fast forward two decades and several financial crises later and it may come as a surprise that few regulators actually define and estimate risk by using probability estimates.[8]

The reasons regulators prefer to assess risk qualitatively and eschew risk quantification varies. Some may regard probability assessment as usurping the role of the regulator in using common sense. Others may believe that risk assessment is the responsibility of the banks and monitoring risk becomes equivalent to monitoring how banks assess risk. Some may conclude that sufficiently precise estimates of probability are unattainable. Still others prefer to rely on measurable historical financial ratios as risk indicators that do not require models. In any event, it can be argued that it is easier for an examiner to determine whether a recent historical accounting ratio such as tier 1 capital to risk weighted assets is inadequate, than it is for an examiner to determine whether the probability of insolvency exceeds a regulatory threshold. The former becomes a comparatively simple "check the box" exercise; the latter requires statistical inference and a stipulated probability threshold.

STANDARDIZED FINANCIAL RATIOS AND PROBABILITY

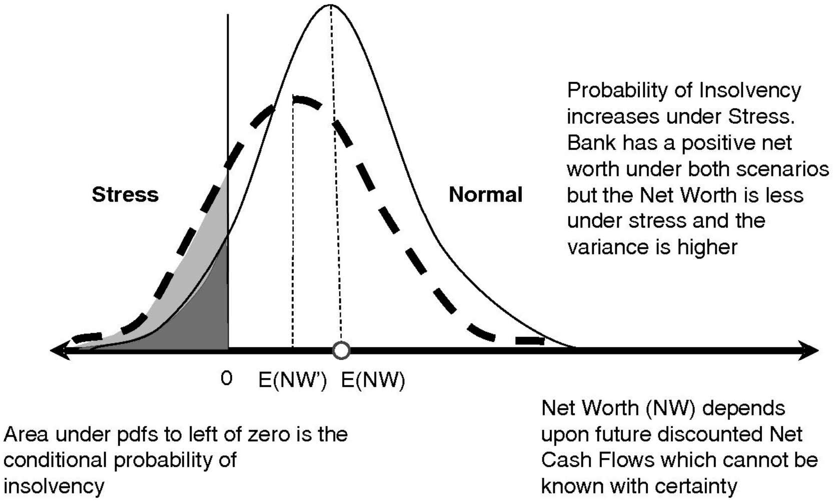
Theory suggests there should be no difference between using standardized financial ratios to monitor risk and using probability of insolvency thresholds. The two should be equivalent where the minimum capital regulatory ratios are derived using a pre-specified probability of insolvency threshold. Jarrow (2012) makes a convincing argument of the inherent duality between the two.[9] Nevertheless, there is a practical difference that undermines this argument. The practical difference has to do with the fact that regulators tend to ignore the probability of insolvency and hold such financial ratio threshold fixed over time. By appealing to Basel or standards set in other countries, regulators avoid estimating the probability of insolvency.

Although it is reasonable to assume that a probability of insolvency threshold may be imposed by a regulator for all banks and that this threshold should remain constant over time, the same cannot be said for financial ratios. The financial ratio thresholds can and should vary when banks adjust portfolios and economic conditions change. Capital adequacy thresholds become inadequate when this occurs. This phenomenon preceded the 2007 financial crisis. Banks determined to be adequately capitalized before the crisis turned out to be inadequately capitalized after the crisis.

Since the 2007 financial crisis, regulators have begun to rely on stress tests of internal bank models to signal the potential for capital and liquidity shortfalls under stressful macroeconomic conditions.[10] Such models are typically capable of forecasting income and balance sheets and associated financial soundness indicators (FSIs). If projections indicate a violation of critical FSI levels, "risks" are said to increase. The outputs of such models have little to do with probability because most scenario analyses are largely deterministic. Deviations between base and stress scenarios are used to determine how much additional capital or liquidity may be necessary should the stressful scenario develop. Considerable attention is being devoted to this issue with an objective of expanding stress tests to consider probability.[11]

CONDITIONAL PROBABILITY OF INSOLVENCY

Although accounting conventions provide an estimate of the net worth of an institution, economics and finance define the net worth of an institution in terms of its future discounted net cash flow. Estimates of the net



Source: Author's calculations.

Figure 10.1 Net worth and the probability of insolvency

worth such as its stock price × shares outstanding, or accounting measures such as book or market value capital provide "best guess" of a bank's net worth, but when net worth is viewed as a future discounted net cash flow then it must be estimated in the context of its conditional probability distribution. As an illustration, consider Figure 10.1.

In Figure 10.1, a bank has an expected positive net worth under either normal or stressful macroeconomic conditions. Its current financial condition, portfolio, and hedging strategy determine its probability distributions under both normal and stressful conditions. Its net worth is lower and its variance greater in the stressful case. The probability of insolvency is greater under stressful conditions than under normal conditions. Monitoring the safety and soundness of any bank requires an understanding of how the probabilities of insolvency may change over time.

Banks estimate credit risk, market risk, operational risk, liquidity risk, and other risks associated with RBS in terms of the potential losses to be borne by the banks themselves. More often than not these risks are estimated separately with no covariance assumed. Again, if the probability of insolvency is viewed as the safety and soundness metric, all such risks become subsumed in their marginal effects on probability of insolvency. Changes in the probability of insolvency with respect to asset quality become credit risk measures. Changes in the probability of insolvency with respect to interest rate and foreign exchange rates become measure of market risk. Changes in the probability of insolvency with respect to management characteristics become measures of operational risk. Changes in the probability of insolvency with respect to earnings and liquidity become measures of earnings and liquidity risk.

Ironically, banks are less focused on estimating the probability of insolvency than the probability of achieving higher returns and near term net cash flows. Few regulators require banks to submit probability of insolvency estimates and larger banks who consider themselves "too big to fail" may discount the need to estimate the likelihood of insolvency. Regulators, however, must be able to estimate the probability of insolvency and determine risk impacts using a relatively broader scale to determine who bears the losses and how large the losses may be.

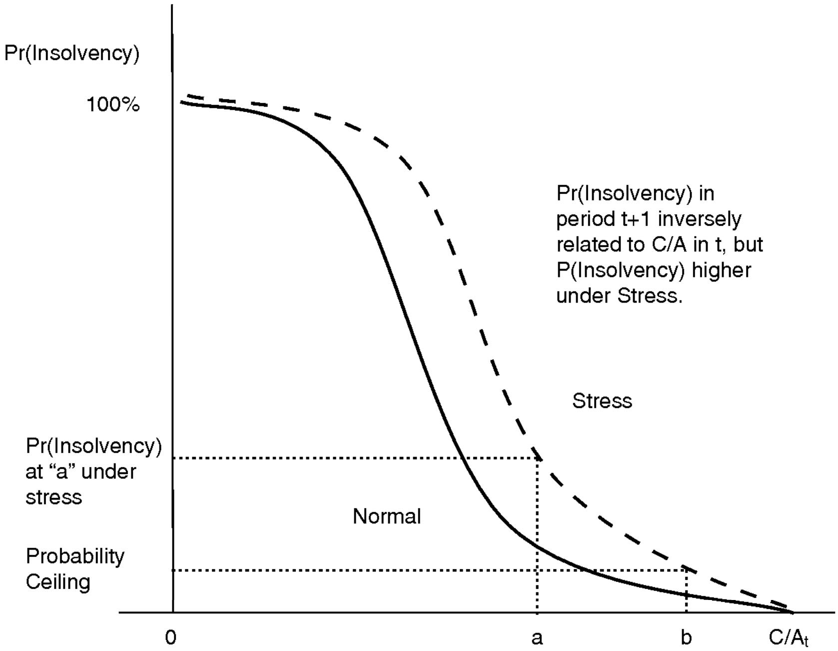
Regulators mandated to monitor the safety and soundness of banks may estimate the conditional probabilities of insolvency using a variety of analytical techniques including distance to default models, stochastic asset liability models, and limited dependent variable econometric models. The estimated probability of insolvency in conjunction with a loss given insolvency provides an estimate of expected future losses or magnitude risk.

PROBABILITY OF INSOLVENCY AND CAPITAL ADEQUACY

The accounting of a bank's capital as an identity comprised of on- and off-balance sheet assets less liabilities (on a book or market basis) makes capital asset ratios prominent risk indicators. A compelling case can be made that as the capital to asset ratio approaches zero in a given period insolvency frequently results in a subsequent period. The Basel Accords I, II, and III suggest minimum capital and liquidity ratios should be used as safe and soundness standards. On-site and off-site examiners compare recent ratios to such standards to determine whether a bank is in compliance with safe and sound practices.

Unfortunately, regulators do not typically establish a probability of insolvency threshold from which they derive minimum capital adequacy or liquidity thresholds. Regulators often use criteria and standards cited in the Basel Accords. As a result, the minimum regulatory ratios used such as tier I capital to risk weighted assets appear fixed over time. Competition among banks tends to push banks to operate collectively close to the regulatory standards and adverse shocks tend to increase the probabilities of insolvency during stressful conditions. See Figure 10.2.

In Figure 10.2 the P(Insolvency) or $P(NW < 0)$ in period $t + 1$ is inversely



Source: *Author's calculations.*

Figure 10.2 P(Insolvency) and minimum capital ratio

related to a capital asset ratio in period t given future macroeconomic conditions in period t + 1.

Under normal conditions a threshold probability for P(NW < 0) may be uniquely related to a minimum capital ratio at "a." Banks with minimum capital ratios exceeding "a" have a probability of insolvency less than the maximum regulatory threshold. Those with capital asset ratios less than "a" have a probability of insolvency that exceeds a regulatory maximum. Those with capital asset ratios greater than "a" are assumed to be adequately capitalized, but unfortunately other factors affect the likelihood of insolvency in period t + 1 like macroeconomic conditions.

If stressful conditions were to develop in period t + 1, the minimum capital ratio imposed in period t would have to be increased to "b" as the "S" curve shifts to the right.

Assuming, however, that minimum capital ratio was to be inappropriately held at "a" and stressful conditions were to develop, even banks that satisfied the minimum capital ratio in period t would exhibit a probability of insolvency that would violate the probability threshold. During the last financial crisis, for example, many banks that required regulatory bailouts and held inadequate capital, had satisfied the minimum capital requirements entering the period.

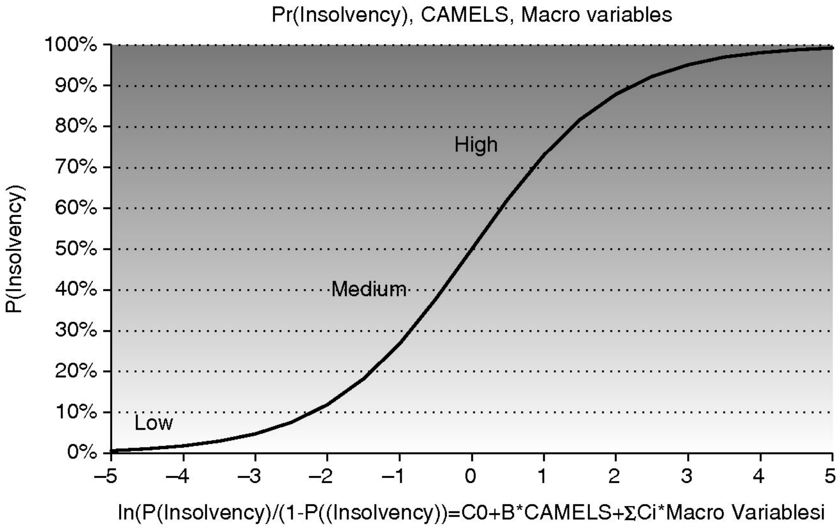
Although it is possible to develop minimum capital ratios based upon bank peer groups and prior history without explicit consideration of the probability of insolvency, the two concepts are intertwined. This should come as no surprise given the regularity of banking crises and macroeconomic cycles. "After the fact" safety and soundness violations increase when the probability of insolvency is ignored or underestimated and capital asset thresholds understate the actual probabilities of insolvency.

SCORING MODELS AND THE PROBABILITY OF INSOLVENCY

Bank regulators have used on-site scoring models like CAMELS to rank banks since the 1980s and before RBS became popular.[12] These scores depend upon FSIs such as capital asset ratios, non-performing loans to total loans, returns on assets and equity, duration ratios and other variables. The International Monetary Fund (IMF) has devoted a website to such FSIs organized into CAMELS components, and provides technical assistance to member countries seeking to construct such systems.[13] Financial soundness indicators traditionally consist of backward-looking financial ratios derived from income and balance sheets and information obtained from recent on-site examinations, including management assessments. Conceptually, FSIs need not be restricted to backward-looking ratios. Bank business plans provide an example of forward-looking FSIs. Deviations between projected FSIs and actual FSIs provide a basis for assessing bank risk management.

Scoring models rely on FSIs to construct numerical indices which provide an assessment of the current financial condition of banks. A few regulators insist on using consistent and systematic scoring by choosing weights and critical values for the FSIs that would permit scores to be replicated and tested. The virtue of such scoring models is that they provide a formal process to convert large sets of quantitative and qualitative assessments into a single index. Off-site and on-site models should produce similar scores. Such models need not be complicated and may be as simple as a weighted average of normalized FSIs. Ultimately CAMELS scores rise and fall as FSIs change.

The scoring models provide an assessment of the current financial condition of the bank, not a risk assessment. The current financial



Source: Author's calculations.

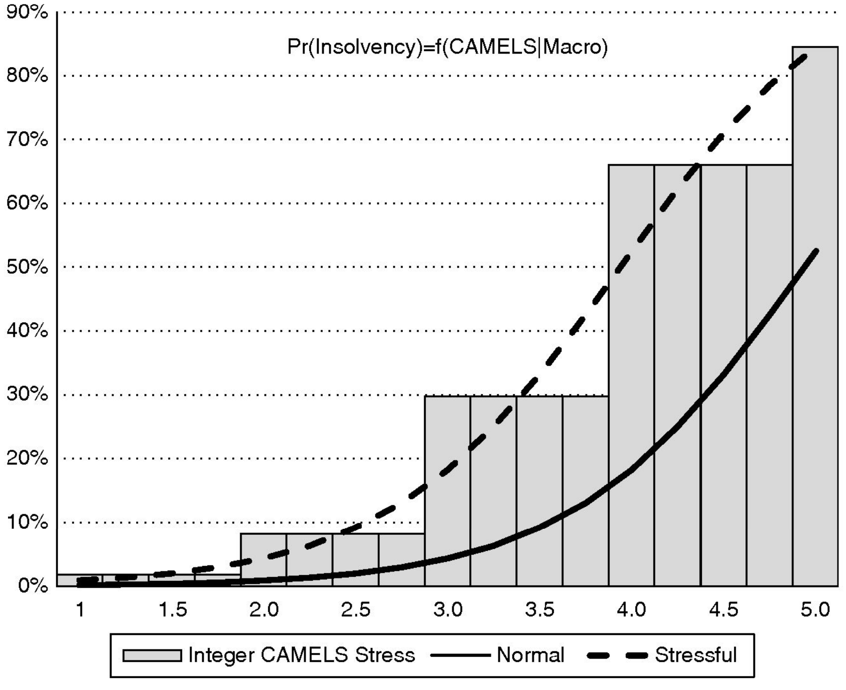
Figure 10.3 Probability of insolvency

condition of the bank, however, has implications for the probability of future insolvency.

Banks that exhibit an increase in a CAMELS score from one period to the next are assumed to be riskier, all else being equal. A bank in worse financial condition should have a higher likelihood of insolvency over a future period than a bank in a better financial condition.

The question remains, however, "how much higher?" One of the simpler analytical techniques that may be employed to answer this question is to use a logistics function.[14] A cross-section and time series panel data set of CAMELS scores and selected macroeconomic variables provides a vehicle to estimate and monitor the conditional probability of insolvency while requiring comparatively few parameters to be estimated.

The log ratio of the probability of insolvency relative to the probability of solvency may be expressed as a linear function of CAMELS ratings and selected macroeconomic variables. See Figure 10.3. This function permits regulators to estimate the probability of insolvency with a single equation and relatively few parameters. Note that regulators may still use a heat map as a backdrop for the function where colors are scaled with probability levels. The function maps any bank at any time period with a CAMELS rating given a subsequent macroeconomic scenario. The logistics function



Source: Author's calculations.

Figure 10.4 Probability of insolvency and CAMELS ratings

provides a stationary "S" curve. See Figure 10.3. Regulators need only estimate the coefficients, C0, C1,. . .,CN, and **B** to estimate the probability of insolvency. For example, five macroeconomic variables, a CAMELS rating, and an intercept requires estimating only seven coefficients.

The coefficient, **B**, should be positive if the scoring model works as expected; increases in CAMELS ratings should increase the conditional probability of insolvency. Under normal or baseline macroeconomic conditions the probability of insolvency would be expected to be lower than the probability of insolvency under more stressful conditions. See Figure 10.4.

The probability of insolvency over a finite forecasting period ranges between 0 and 1. A CAMELS rating that provides an index of a bank's financial condition ranges from 1 to 5. All banks within a given population of banks are assigned a CAMELS rating and can be assumed to lie on a given "S" curve that reflects future macroeconomic conditions. The solid line in Figure 10.4 reflects normal conditions where the probability ranges from 0.1 percent to roughly 55 percent as CAMELS ratings increase from 1 to 5. The dashed line reflects stressful conditions where the probability ranges from 1 percent to over 80 percent. The differences in estimated probabilities of insolvency for a given CAMELS ratings increase dramatically for CAMELS in the 2.5 to 4 range.

Figure 10.4 illustrates how the probability of insolvency in a future period, say 12 months, may be related to each bank under normal and stressful macroeconomic conditions. Each bank consequently would have a range of estimated probabilities of insolvency in period t + 1 for any given CAMELS score in period t. Regulators using a continuous measure of CAMELS ratings have an advantage over those who restrict the CAMELS ratings to integers.

The shape of the "S" curve reflects the assumption that banks with a CAMELS rating of less than 2 exhibit relatively small changes in the probabilities of insolvency, but as the scores increase from 2 to 4 the probabilities of insolvency increase dramatically, tapering off before the CAMELS scores reach 5. The steepness of the assent in Figure 10.4 is reflected by the estimated magnitude of the B coefficient associated with the CAMELS ratings; the larger the coefficient the higher the probability of insolvency associated with a given CAMELS rating.

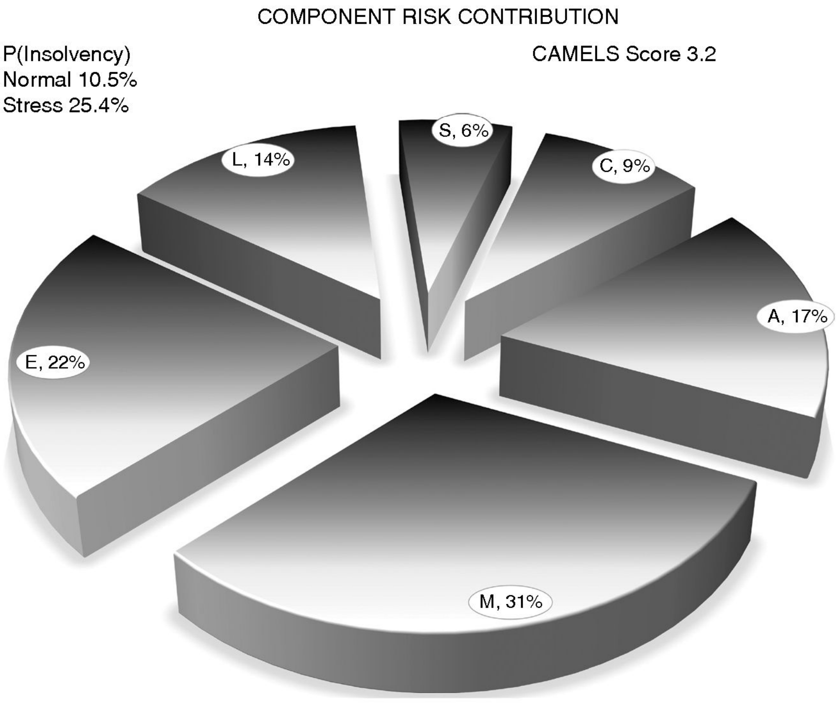
Regulators may estimate the functions in Figures 10.3 and 10.4 function using econometrics software that is readily available.[15] To prepare the panel data for the econometrics estimations, regulators combine time series panel data for each of the banks. Banks that historically become insolvent, exhibit a negative book value of capital, or possess other characteristics of bank failure receive a value of 1 and others a value of 0. Macroeconomic variables for the interim period are added to the panel data set. Once the sample is collected, a single equation logit function may be used to estimate the coefficients in Figures 10.3 and 10.4. The estimated coefficients can be subsequently validated using hypothesis testing and analysis of type I and II forecasting errors with data in and out of sample.

Because central banks typically employ macroeconomic forecasting models that are used to provide stressful macroeconomic variable projections, projections of macroeconomic variables to estimate probability of insolvency in future periods become readily available. Those estimated probabilities may in turn be shared among off-site and on-site examiners to be used in the monitoring of risk. Regulators may establish different probability thresholds for baseline and stressful conditions as criteria to flag excessive risks.

HOW THE PROBABILITY OF INSOLVENCY ESTIMATES MAY BE USED

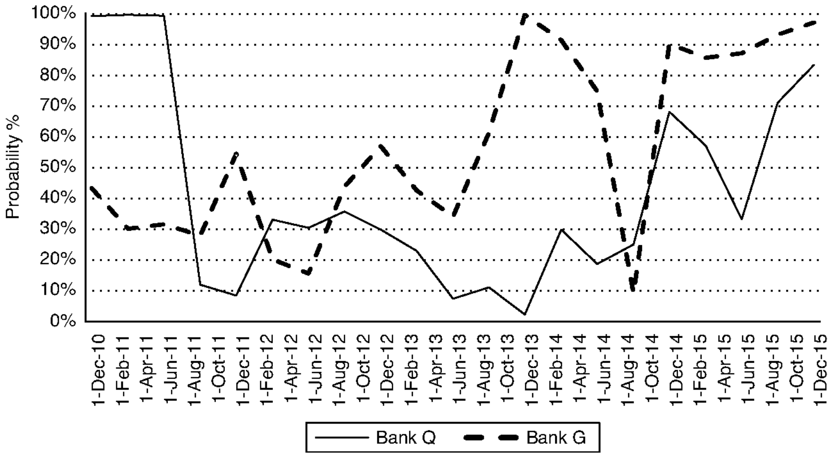
Once the relationship between probability and current financial conditions has been estimated and validated, regulators may use these results to flag problem banks on a forward-looking basis because they can estimate the direction and magnitude of risk. These results provide a risk-based monitoring system that may be used to schedule examinations and focus the examinations on particular CAMELS components. See Figure 10.5.

Consider a bank that has a CAMELS score of 3.2 based upon an estimated and validated logit function with an estimated probability of insolvency of 10.5 percent in the base case and 25.4 percent in the stressful case. The largest contribution of CAMELS components to the estimated probability of insolvency is the "M" or management ratings at 32 percent, followed by earnings at 22 percent, asset quality at 17 percent, liquidity at



Source: Author's calculations.

Figure 10.5 CAMELS components risk contribution



Source: Author's calculations.

Figure 10.6 Probability trends

14 percent, capital at 9 percent, and sensitivity to market risk at 6 percent. The contribution of the shares depends on the weights and critical values attributed to the FSIs. The probability of insolvency depends on the CAMELS rating and macroeconomic scenarios. Information like that contained in Figure 10.5 should be available quarterly for each bank with a RBS monitoring system.

In addition to CAMELS component contributions to risk, regulators may also obtain the contributions of each FSI on the estimated probabilities of insolvency given the weights and critical values of the FSIs. These are contained within the CAMELS ratings and the sensitivity of the probability of insolvency to the aggregate CAMELS ratings. Such estimates may also be used to estimate credit risk, management (operational risk), earnings risk, liquidity risk, and market risk in a consistent basis by using estimates of how the FSIs are linked specifically to the conditional probability of insolvency.

By decomposing risk in this fashion, regulators can use this information to develop a course of action to mitigate risk. For example, regulators may explore the degree to which the FSIs and components may be substituted to maintain a probability of insolvency threshold. In this case improvements in asset quality, provisioning, hedging, and other strategies may provide alternatives to increasing capital or liquidity to comply with a probability threshold. Banks should be able to reduce a probability of insolvency to satisfy regulatory constraints in a least cost manner using the shadow prices associated with CAMELS components and FSIs.

Monitoring risks systematically can be accomplished by using dashboards that provide user-friendly risk monitoring information to on-site and off-site examiners. Such dashboards are well within the scope and skill sets of information technology exhibited in many regulatory institutions. See Figure 10.6 for an example of a dashboard output.

Figure 10.6 depicts how the probability of two banks becoming book value insolvent occurred over a recent historical period based on a model similar to that in Figures 10.3 and 10.4. Such "probability" trends can provide timely risk flags for banks that explicitly link CAMELS ratings to probabilities. The examiners may choose which banks and time periods to compare with a point a click approach.

Depending upon the number of banks regulated and the accuracy and timeliness of the FSIs, such dashboards should provide a convenient way to improve risk monitoring and synthesize risk.

Dashboards have become essential components of risk monitoring systems, particularly if risk is viewed as a conditional probability of future losses. Probability estimates, although based on FSIs, scoring models, and macroeconomic considerations, are not as intuitive nor as appealing to RBS regulators and observable as capital adequacy and liquidity ratios. However, such estimates should be basic to risk monitoring and provide RBS regulators with enhanced risk assessment tools. If the analytics associated with probability of insolvency are easily accessed using dashboards, such estimates should become more routine components of RBS risk monitoring.

CONCLUSION

While individual banks have a comparative advantage to estimate the probabilities of their rates of return on assets and equity, regulators should have a comparative advantage in estimating the likelihood of insolvency based on their forensic examinations of previous bank failures. Regulators by virtue of on-site examinations should have information that, used in conjunction with market information, should permit regulators to estimate the conditional probabilities of insolvency for regulated banks and use these estimates in the process of risk monitoring.

As the name indicates, RBS should be able to define, estimate, and quantify risk in terms of its direction and magnitude as part of routine risk monitoring. This quantification requires bank regulators to estimate the conditional probability of insolvency for each of their banks on a systematic basis. As this chapter suggests, regulators can exploit existing regulatory tools such as CAMELS ratings, long familiar to on-site and off-site examiners, to estimate such probabilities and validate risk assessments. Examiners may continue to use scoring models and heat maps, but these must be enhanced by more quantitative risk assessments. Improvements in FSIs such as incorporating bank business plans and stochastic stress tests will only accelerate this process and continue improve regulatory risk monitoring under RBS.

Estimating the probability of events that can result in future losses will always be a challenge, yet failing to estimate such probabilities is difficult to excuse given the stated objectives of RBS and the magnitude of losses associated with recent banking crises.

NOTES

1. See the Office of the Comptrollers handbook on risk based supervision, accessed December 2016 at https://www.occ.gov/publications/publications-by-type/comptrollers-handbook/pub-ch-ep-bsp.pdf. Risk assessment involves identification and quantification. Risk identification requires an enumeration of hazardous events and incidents that could result in losses. Risk quantification requires estimation of the likelihood/probability of this scenario, an assessment of the impacts/loss associated with the risks.
2. Faulk, Betsy and Walter Faulk, "Cradle-to-grave approach to bank supervision," September 2016 PowerPoint presentation prepared for the International Monetary Fund (IMF), emphasizes the importance of licensing and requiring bank business plans as components of risk-based supervision.
3. Heat maps process may allow individual examiner biases to affect the risk assessment and in a committee structure but they may foster "group thinking." Scales used to formulate "high," "medium," and "low" severity and likelihood are often misunderstood and seldom documented. Qualitative risk assessments at a point in time often fail to indicate whether a risk is increasing or decreasing within a specific category. For example, a bank with a "high" risk in two successive periods does not indicate whether the risk direction may be slightly increasing or decreasing. Qualitative assessments seldom provide sufficient information concerning different types of risks or interactions across risk categories, nor do they provide an ability to learn from forecasting errors. Most importantly, however, such tools do not provide information about exposures to extreme events. Regulators have a tendency to discount "high impact, low-likelihood risks" risks. Finally, qualitative assessments provide insufficient information as to the best course of action to lower either the direction or magnitude of the risks.
4. Published by Houghton Mifflin, Boston, MA.
5. Machina, Mark J. and Michael Rothschild (2008), "Risk," in Steven N. Durlauf and Lawrence E. Blume (eds), *The New Palgrave Dictionary of Economics*, 2nd edn, Palgrave Macmillan. *The New Palgrave Dictionary of Economics Online*. Palgrave Macmillan, doi:10.1057/9780230226203.1442.
6. The Basel Committee on Bank Supervision website provides documentation for the Basel I, II, and III Accords, accessed January 2017 at http://www.bis.org/bcbs/. Core Principles 8, 9, and 10 pertain to off-site bank supervision and risk assessments.
7. Kamakura Corporation offers firm specific default rates, accessed January 2017 at http://kamakuraco.com/Solutions/DefaultProbabilities.aspx. Moody's also offers firm specific default rates, accessed January 2017 at https://www.moodys.com/sites/products/DefaultResearch/2006200000425249.pdf.

8. There appears to be no formal survey of early warning systems and risk estimation within RBS countries since the BIS survey in 2000. See http://www.bis.org/publ/bcbs_wp4.pdf (accessed February 2017). The observation that many regulators fail to include probability estimates as part of the monitoring process comes from the review of many bank supervision manuals and the experience of technical experts serving on IMF RBS missions. It is often difficult to find documentation that provided directions to examiners as to how to specifically define and estimate risk. Frequently the same issue extends to scoring models like CAMELS where weights and critical values of FSIs are not standardized.
9. Jarrod, Robert, "Capital adequacy rules, catastrophic firm failure, and systemic risk". Johnson School Research Paper Series No. 5-2012, 12 June 2012, accessed December 2016 at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2084200.
10. See the electronic library established by the IMF for stress testing, accessed February 2016 at http://www.elibrary.imf.org/page/stress-test-toolkit?redirect=true. Stress tests provide useful simulations that provide comparative static and dynamic representations of potential losses to capital and liquidity relative to shocks. The IMF library includes examples of spread sheets that regulators may choose to employ for monitoring individual banks as part of RBS.
11. Schuermann, T., "Stress testing banks," Wharton Financial Institutions Center, 2013, accessed January 2017 at http://fic.wharton.upenn.edu/fic/papers/12/12-08.pdf.
12. Sahiwal, Ranjana and Paul Van den Bergh, "Supervisory risk assessment and early warning systems," Bank of International Settlements, Working Paper Series, December 2000, accessed January 2017 at http://www.bis.org/publ/bcbs_wp4.htm.
13. See https://www.imf.org/external/np/sta/fsi/eng/fsi.htm (accessed December 2016). Regulators in many countries use the list of FSIs to construct scoring models using weights and critical ratios appropriate to each country.
14. Cramer, J.S. (2003) *Logit Models from Economics and Other Fields*, accessed January 2017 at https://www.cambridge.org/core/books/logit-models-from-economics-and-other-fields/510D1D6FF8E2B6D6C80FEF7B4697EAB7.
15. STATA, EVIEWS, SAS, SPSS, and other commercial econometrics packages offer maximum likelihood estimators to estimate the coefficients for the "S" curves in Figures 10.4 and 10.5 with bank panel data.