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I. Background

The recent financial crisis in the U.S. has been characterized by declining asset values and increasing levels of credit default in the banking sector. Bank losses and insolvency, declines in credit availability, damaged investor confidence, and decreased capacity of borrowers to repay loans have all had a negative impact on banks during this period. Although community banks do not manage the complicated financial products or the large portfolios of home loans that have precipitated the financial crisis, they are becoming more integrated into capital markets and they are not immune to the consequences of these adverse events. Community banks also typically have fewer resources with which to adjust to major changes in the financial marketplace.

One approach to this problem is for community banks to develop and apply methods of portfolio analysis and stress tests that provide them with timely information on their risk exposures and potential losses. The aim of these methods might be to maximize the expected return to the portfolio while keeping the risk exposure at acceptable levels. This approach requires the use of methods and tools that provide information on exposures and how to balance return and risk within the portfolio, how to calculate the levels of economic capital required, and how to set individual borrower and portfolio-level concentration limits.

Some banks have begun to develop formal methods and tools to assess risk exposure and perform stress tests of their portfolios, and large banks are further ahead in this effort. Yet, all banks are being driven by economic uncertainty to do more to assess their portfolio risks. An additional driver of this process is bank regulatory and supervisory agencies that are requiring banks to measure their credit risks and document the methods they use to monitor their loan portfolios and to establish their provisions for loan losses. In addition, as banks look to the interbank market for financing of their participation loans, the banks themselves are requiring more of this type of information from each other before entering into joint lending arrangements.

Objective

In this paper we identify the gap between the existing research literature on this topic and the approaches and methods that community banks actually use to evaluate credit risk in their loan portfolios, particularly their agricultural portfolios. To reach that goal we propose to: 1) selectively review the research literature on bank agricultural portfolio risk analysis and 2) identify the set of methods that community bankers currently use for portfolio risk analysis. In a second paper we propose a methodology for portfolio analysis that will help to bridge the gap between what the research suggests be done and what bankers do. In that paper we use visual portfolio analysis to illustrate how community bankers can analyze their risk exposure and migration patterns.

Section II of this paper is structured around a selective review of the applied research literature on credit risk analysis. Section III summarizes the methods that bankers report using when they conduct a portfolio risk analysis, e.g. trend or benchmark analysis (portfolio tracking) and stress-testing analysis (portfolio shocking). Section IV provides a set of concluding comments.

II. The Literature

The research literature on portfolio risk analysis breaks down into roughly four segments: credit scoring models, credit risk migration analysis, credit risk models, and portfolio simulation models.

Credit Scoring

Pederson and Chellappan (1991) provide the summary of a banker survey on credit scoring methods that agricultural bankers use. The survey suggests that the primary reasons for developing credit scoring information on individual clients is to use it as a basis for a lending decision, for assessing risk in the overall loan portfolio, and for establishing borrower credit limits or interest rates. Based on that report, the characteristics that banks follow in their credit scoring models (and the percentage of banks using them) include: liquidity (100%), solvency (100%), collateral (100%), repayment capacity (100%), management ability and character of the borrower (52%), financial and operating efficiency (30%), profitability (16%), and various other factors (67%). The survey reveals a wide variety of formal and informal methods that banks use to develop credit scores for their agricultural clients.

Gustafson, Pederson and Gloy (2005) review the applied research literature and offer a synthesis of the advances in credit risk assessment. They review the applications of four alternative credit evaluation methods: linear probability analysis, discriminant analysis, probit analysis, and logit analysis. These methods provide similar predictive power. In addition to controlling and monitoring credit risk exposure, they suggest that credit scoring models (CSMs) are useful in assisting in loan approval decisions, pricing loans in which differential interest rates are used to price for risk, and meeting regulatory requirements. The basic steps of developing a credit scoring model are:

1. identify the key factors that best distinguish borrower creditworthiness
2. choose appropriate measures for these variables
3. weight the variables according to their relative importance to the lender
4. score each loan as a weighted average of the respective variables, and
5. assign the credit scores to the appropriate classes of loans (or borrowers).

Credit Risk Migration

Migration analysis is a relatively recent, probability-based measurement concept for credit risk that is consistent with the modern approaches to economic capital management by financial institutions, including those approaches contained in the proposed New Basel Accord (Crouhy, Galai, and Mark, 2000; Barry, 2001; Basel Committee on Banking Supervision, 2009).

Migration analysis is based on extrapolation into the future of historic rates of movement (i.e., transition probabilities) of individual loans among the classes of a lender's risk-rating or credit-scoring system. One result of utilizing the migration concept is a richer, more comprehensive treatment of credit risk and loan losses than relying solely on the measurement of historic default rates. A migration analysis might evaluate how macroeconomic variables such as farmland value, aggregate money supply, the S&P500 index, the long-term interest rate, or consumer prices potentially influence loan risk migration.

According to Stokes and Gloy (2007) the functions of credit risk migration analysis are

- to predict behavior for a class of loans,
- to evaluate effectiveness of and compliance with existing credit policies and risk scoring,
- to identify the risk-rating thresholds at which payoffs or recoveries diminish,
- to calibrate models for probability of default and loss given default, and
- to validate the reserve for future loan losses.

Based on a Markov chain model, they use an entropy-based econometric technique to calculate the probability of default of the transition probabilities in a mortgage portfolio.

Barry, Escalante, and Ellinger (2002), Nickell, Perraudin, and Varotto (2000), and Bangia, Diebold, Kronimus, Schagen and Schuermann (2002) show that the transition probability of retaining the current risk rating is the highest, and these probabilities decrease as the distance between risk classes increases. For example, the probabilities of a farm business migrating to a “near” class are higher than the probabilities of migrating to a “far” class, and they exhibit a higher tendency to downgrade than upgrade. Bangia et al. and Nickell, Perraudin, and Varotto show that transition probabilities should be based on some conditioning factors, such as geographical location of company, type of industry, and macroeconomic business cycle.

Phillips and Katchova (2004) use the Markov property of independence to test for “path dependence” in risk migration data. They find that among farm businesses the Markov property of independence is violated. During the expansion phase, the retention rate of the highest risk class is significantly lower than the unconditional retention rate. However, during the recession phase the retention rate for the highest class is significantly higher than the unconditional retention rate. Their results are consistent with those of previous studies that analyze transition probabilities. Nickell, Perraudin, and Varotto find that transition probabilities of bonds exhibit a higher tendency to upgrade during an expansion but a higher tendency to downgrade during recession. Phillips and Katchova find that the significant transition probabilities in the downward trend and upward trend matrices exhibit a pattern of trend reversal. This means that a downgrade in credit quality last period would more likely result in an upgrade in credit quality over the next period in comparison to an unconditional upgrade. The opposite pattern is present in the upward trend matrix.

Escalante, Barry, Park, and Demir (2004) find that larger farms are more likely to have credit upgrades. The risk migration matrices obtained in this study reflect the expected trend of lower class retention rates and highly volatile transition probabilities compared to results obtained for bonds and other publicly traded securities. Their results show that farm-level factors do not have a large impact on the probability of credit risk migration, but macroeconomic factors do. For example farm real estate values represent a growing economy and a greater likelihood of class upgrades. The relaxation of credit constraints through higher levels of money supply has a similar positive effect on credit risk migration, while a higher interest rate has a negative effect on migration patterns.

Behrens and Pederson (2007) use conditional migration matrices to evaluate path dependence, loan size, and loan seasoning in a large agricultural loan portfolio. They measure risk migration by generating the migration matrix, which has an initial and ending rating, to show the direction and distance of migration. If loans were previously downgraded, the probability of another downgrade is larger than if the loans had been previously upgraded. Retention rates for the highest quality class are generally the largest. They find also that a trend reversal pattern exists. Also, they examine the influence of previous migrations on future migrations for individual loans and alternative lengths of time since origination of the loan.

Loans that migrate in a previous period are more likely to migrate again in the next period, but this is statistically significant only in high credit quality classes. Small loans are less likely to migrate than median-sized loans and median-sized loans are less likely to migrate than large loans. Unseasoned (new) farm loans are more likely to migrate than seasoned farm loans and unseasoned loans have a higher probability of downgrading than seasoned loans.

Deng, Escalante, Barry and Yu (2007) use a time-homogeneous Markov chain model and a time-inhomogeneous model to analyze farm credit migration compared to the discrete-time model. Farm borrower financial information is usually reported on an annual basis and farm lenders typically use multi-year averages when doing credit risk assessment. This may lead to a failure to identify transient changes in the borrower's credit risk quality. The resulting cohort model tends to estimate lower default probability than a Markov model.

Gloy, LaDue and Gunderson (2005) examine credit risk migration using lender risk ratings. They find that these lender ratings are more stable (less likely to migrate) than ratings that are based on credit scores derived from financial statements. They suggest that nonfinancial factors play an important role in assessing credit risk. In addition they use regression analysis to identify several factors that influence the likelihood of credit downgrades. Those factors include the borrower's risk tier, personal characteristics, and the stage of the business life cycle. Interestingly, the primary agricultural enterprise type does not appear to have a significant impact on the likelihood of a credit downgrade.

Credit Risk Portfolio Models

Portfolio models of credit risk exposure do not focus on producing credit scores. Rather, the emphasis is placed on estimating the level of default risk exposure in sub-portfolios and the correlation between those sub-portfolio segments in terms of their likelihood of default.

Zech and Pederson (2004) use a probability density function approach for calculating portfolio-level loan loss. The key inputs of the expected loss function are the probability of default, the loss given default, the exposure at default, and the time horizon (typically one year). Economic capital is approximated as the tail percentile that represents the total amount of risk less the expected loss covered by the loan loss reserve. The shape of the portfolio probability density function is dependent on the portfolio composition: loan default probabilities, relative loan sizes, correlations of default between loans, and concentrations by the number of loans and sector or industry.

They provide a summary of the four major credit risk models KMV Portfolio Manager, Credit Metrics, Credit Portfolio View and CreditRisk+. They argue that the Credit Risk+ model is a better model for agricultural lenders. The Credit Risk+ model is enhanced by using an alternative solution algorithm and by accounting for correlations between sectors. Model inputs are the net loan loss exposure, default rates and their volatilities, and correlations of loan default between industries. The model output is the expected loan loss (EL) and the unexpected loan loss (UL), each of which can be decomposed into loan risk contributions by industry or portfolio segment. The model generates portfolio, sub-portfolio, and loan-level risk measures. They use lender historical data to calculate risk migration. The effect of loan risk migration is included in the estimates of default rates and volatilities. The paper also uses historical data to estimate correlations between industry defaults. Stress-testing is done with the model to compare the base scenario to alternative high- and low-stress scenarios when the loan risk ratings and loss given default (LGD) ratings change.

Katchova and Barry (2005) develop a credit risk model based on Merton's pricing approach. That is, default occurs when a farmer misses a debt payment, but if the farm is solvent the debt can be refinanced. The paper illustrates how to calculate probability of default (PD), loss given default (LGD), expected loss (EL), and unexpected loss (UL) using farm-level business reporting data and several additional assumptions about the credit scoring model used by an agricultural lender in order to estimate the PD parameters. They include calculation of the standard deviation of default and default correlations. The statistical probability of default for each farm is calculated using the probabilities of the normal distribution as the probability that assets will fall below the level of debt. The average probability of default is calculated as the weighted average of the probability of default for all farms, weighted by the debt for each farm. Some studies use historical data to calculate PD. This can be calculated as either the percent debts in default or as the percent of farms in default. The loss-based method uses historical data on default and loss given default.

Katchova and Barry classify borrowers into credit quality classes. As in most credit risk models, the advantage of credit quality classes is that the grouping of homogeneous borrowers allows more precise estimation of PD and LGD. The disadvantages are that the precision of assigning borrowers into the appropriate credit quality classes decreases and that a large number of observations are needed to obtain reliable results for each credit quality class. Unlike Credit Metrics, which uses data from rating agencies with established credit quality classes, KMV uses endogenous models to group borrowers. The average PD is calculated as the statistical probability of default and as the historical default rate. A statistical PD is calculated for each farm using the properties of the normal distribution and the farm values of assets, debt, and standard deviation of assets. The LGD is calculated for each defaulting farm as the percentage shortfall of recovered assets below the level of debt. The probability of default and losses are shown to vary among credit quality classes.

Pederson and Zech (2009) suggest that Merton-type models require lenders to employ relatively strong assumptions about the underlying stochastic process for agricultural asset prices and what constitutes a default event in an agricultural loan portfolio. They propose an alternative model based on CreditRisk+ that is adaptable for agricultural lenders.

The CreditRisk+ model allows lenders to estimate the probability distributions of credit losses conditional on portfolio composition by using lender historical loan data, adjusting the PD and LGD for risk migration and variation through the economic cycle of the agricultural industry, and incorporating correlation relationships between identifiable sectors in the loan portfolio. The LGD rate is determined by loan-specific characteristics (e.g., collateral or guarantees). PD for each exposure is determined by the borrower’s risk rating, as evaluated by the lender. The variance of the portfolio PD is represented by the sum of two risks, systematic risk and nonsystematic risk. Systematic risk is due to correlated defaults in the portfolio caused by the risk factors. Nonsystematic risk is borrower-specific risk. The loan loss allowance requirement is equal to the mean of the loss distribution (the expected loss), while the economic capital requirement is equal to the tail percentage minus the mean. Pederson and Zech illustrate the value of expected loss and the unexpected loss of the portfolio as the area under the loan loss distribution curve. The paper uses the farmer bankruptcy rate as an indicator of economic cycles in agriculture. This is because the estimated PDs should reflect a long run estimate of default over the economic cycle, which is necessary for implementing the New Basel Accord. They use value-at-risk (VaR) to measure the level of economic capital required at various levels of confidence.

Peura and Jokivuolle (2004) also use probabilistic value-at-risk (VaR) type criterion to measure the sufficiency of actual bank capital against minimum capital requirements over a defined horizon. This method of stress-testing is an extension of a typical credit portfolio model, simulating actual bank capital and minimum capital requirements simultaneously. The required capital buffer is measured given a confidence level for capital adequacy chosen by bank management.

Portfolio-level Simulation Models

Pederson and Wilberding (1999) explore the methods developed by McKinley and Barrickman (1994) to decompose portfolio credit risk into: transaction risk, intrinsic risk, and concentration risk. Transaction risks are those associated with individual clients and they are captured by each borrower's credit risk rating. Intrinsic risk is identified at the sub-portfolio level by industry type (e.g., some of agricultural bank customers mainly produce dairy or grain products) or by line of business (e.g., operating loans, mortgages). Concentration risk looks at the largest line of business, or by industry, or by largest borrowers. This method produces a risk profile of the bank and a numerical index score which can be compared across different transaction, intrinsic and concentration risk profiles. It also provides a means for assessing risk exposure at the sub-portfolio level (e.g. dairy). The paper also illustrates the use of stress-testing by allocating risks into a systematic category (driven by economy-wide factors) and a nonsystematic category (driven by the characteristics of individual firms). The economy wide factors may be policy shocks (e.g., monetary policy and farm policy) or productivity shocks (e.g., factor productivity, cost of energy).

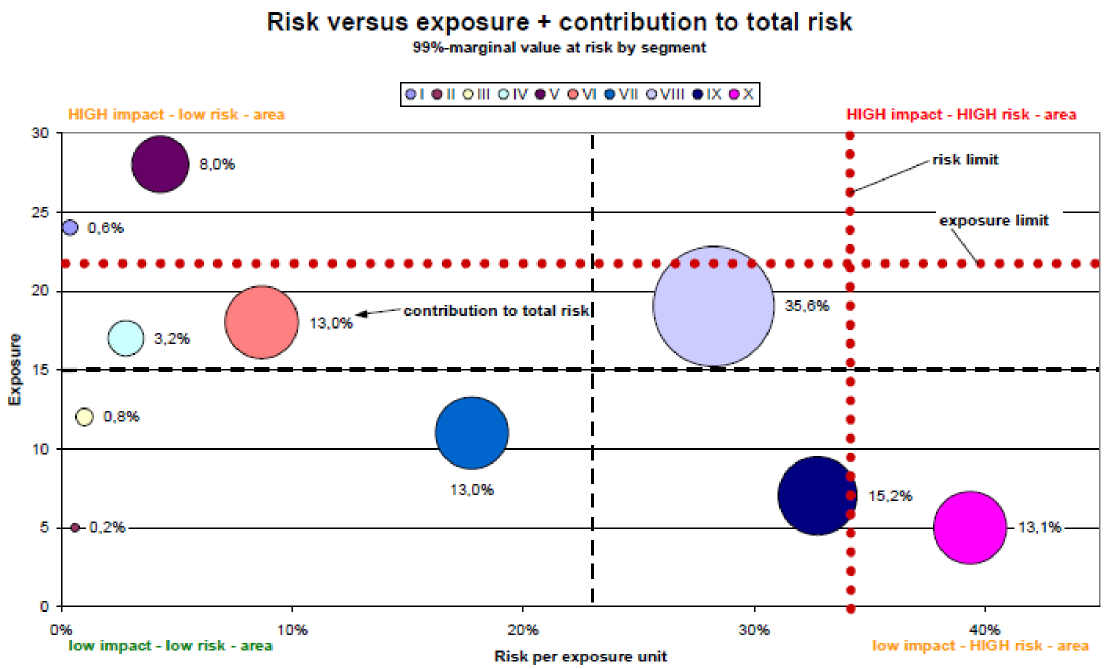
Sakaimbo and Pederson (2011) develop an Excel-based empirical model that agricultural lenders might use to evaluate the capital requirement under the Basel Accord. It decomposes the correlation between PD and LGD into their systematic and nonsystematic components. The random variables are assumed to follow a standard-normal distribution. The analysis uses the Miu-Ozdemir (2005) model approach to calculate correlations between the factors, including PD and LGD for each borrower, the correlation due to systematic risk factors, and the correlation due to idiosyncratic risk factors. Sakaimbo and Pederson subject a portfolio of borrowers to the same systematic risk, while allowing their respective idiosyncratic risks to change. They assume that variations in agricultural land values are a good indicator for the systematic risk factor, which drives PD and LGD at the industry and lender levels. They simulate the effects of an economic cycle on the agricultural lender's portfolio and economic capital.

The model measures the correlations between land values and PD, between land values and LGD, and between PD and LGD. Initially, they assume that any individual borrower has a low-to-moderate borrower specific risk of default, and that the idiosyncratic risks are of equal magnitude. They also do stress testing for the loan portfolio by making specific percentage changes in land values. An interesting point is to evaluate the economic capital requirement as land values decline. For each percentage point decline, they evaluate the percentage mark-up of economic capital that is required to increase capital from the baseline level to that of the relatively stressed level.

Wehrspohn (2003) describes a visual portfolio simulation model in which it is possible to simulate credit risk exposure by loan segment, contributions to marginal risk, and the expected risk-adjusted return on capital (RAROC) of the bank. Marginal risk exposure is identified at the segment (sub-portfolio) level, where risk contribution is measured as the marginal risk conditional on default of a specified portfolio segment. The model allows for a comparison of risk concentration with exposure concentration. Bankers can also set limits to risk concentration by not allowing concentration to exceed a designated percentage of the total risk in one segment.

Wehrspohn visually combines these three indicators in one graph (see Figure 1). Size "bubbles" are used to illustrate the risk concentration of each segment and the bank can set absolute exposure limits. The risk per exposure unit can also be set according to a limit. These combinations of exposure and marginal risk act as the bank's early warning system of portfolio risk.

Figure1: Risk versus exposure and risk concentration (Source: Wehrspohn, 2003, p. ___)



Wehrspohn defines the expected RAROC as the contractual interest rate less the cost of refinancing, operating expenses, cost of default risk, and the cost of equity-target return on equity. The amount of economic capital is calculated from the marginal value-at-risk. Wehrspohn illustrates RAROC and three types of limits in one plot. The model allows one to set three types of limits: the "RAROC limit" (the bank's target return on equity), the "stop loss limit" (the intended target return on equity), and the "destruction limit" (the expected return on equity when it becomes negative). Wehrspohn combines these graphically to visually identify the risk-return trade-off that exists in the credit portfolio.

The visual approach to bank portfolio simulation as developed by Wehrspohn is unique. Although the examples he provides use bond portfolios, the tool would presumably allow banks to develop their own segments based on their portfolio structure. Thus, banks may choose to evaluate different industries and different loan types. The input requirements of the model (at the segment level) include estimates of default probability, total exposure, amounts of guarantees and unsecured exposures, loss given default, and correlation within segments. Thus, a bank may include information about the correlation structure and capture the effect of systematic risk within each sector. This model approach may be adaptable for community banks, as they may lack sufficient historical data to apply other credit risk models that have more stringent data requirements.

III. The Methods Bankers Use

The preceding summary of the research literature shows that there are several methods and tools that can be implemented in portfolio analysis. Yet, it is equally important to investigate how smaller community banks actually perform portfolio risk analysis. In this section we explore if there is a gap between the tools that are provided in the research literature and what these bankers currently do in practice.

In order to discuss this question and better understand how community banks work, we performed a nonrandom survey of eight community banks in the Midwest to learn about what they do when they assess credit risk and what their attitude is toward portfolio risk analysis. Our summary is based on seven bank responses. We believe these responses are representative of community banks in the region.

Generally, community banks reveal that an interim portfolio analysis helps them predict how the current year's profitability is going. It may be used also to make some predictions about the next year. More specifically, bank respondents want to determine if the upcoming year will be a challenge for their customers. Bankers also respond that portfolio risk analysis helps them to identify credit concentrations which they may track as an early warning system.

In our survey of community banks, the most often reported tools are generally credit risk scoring, watch lists, stress tests, and trend (benchmark) analyses. The banks respond that the analysis is aimed at reducing or eliminating risk in certain areas to manage the overall risk exposure in the bank. They indicate that these efforts to assess risk help them to develop early signals of deterioration in key areas of the overall portfolio.

Why might banks use stress analysis?

The objective of a stress test is to understand the sensitivity of the portfolio to changes in various specific risk factors in the bank. The results of a stress test may focus on measure of bank performance or on the performance of clients of the bank. Bankers also use trend (or benchmark) analysis to identify high risk customers. Here the performance of an individual client may be compared to their own past performance (to observe deviations from trend), or a reference group (a peer group, or benchmark), or the whole portfolio.

Stress-testing has become a standard risk assessment technique for banks. Banks use stress tests to understand the firm's risk profile and communicate with senior management. It can be used to forecast financial conditions of the bank, as well as to obtain relatively early warnings of unusual performance. Stress-testing can help banks to set lending limits, to allocate capital, and to enter into hedge positions.

A stress test of bank performance is commonly described as an evaluation of a bank's financial position under a severe, but plausible, scenario. The methods of stress testing are designed: 1) to assess changes in asset quality (e.g., forecast future levels of past-due loans), 2) to evaluate past deviations and spot potential problems (using residual analysis), and 3) to assess changes in risk sensitivity of assets (i.e., to stress-test assets). Stress testing is also used to refer not only to the mechanics of applying specific individual tests, but also to the wider environment (scenarios) within which the tests are developed, evaluated, and used. The information provided by a set of stress tests can also help to identify weaknesses in data collection, reporting systems, and risk management.

It appears that stress testing has become an integral part of risk assessment and bank management strategy. By interpreting the results of stress tests, banks can take into account their position in the market, their particular approach to stress test implementation, and the strategic aspects of risk management. And it may act as a cross-check for other types of analyses. Stress testing alerts bank management to adverse unexpected outcomes related to a variety of risks and provides an indication of how much capital might be needed to absorb losses if large shocks occur. While stress tests provide an indication of the appropriate level of capital necessary to endure deteriorating economic conditions, a bank alternatively may employ other actions in order to help mitigate increasing levels of risk.

Stress tests can include existing and potential market, credit, operational, and liquidity risks. The object of stress-testing could be asset values, profit and loss, economic capital requirements, liquidity, or counterparty risk exposure. Reverse stress tests start from a known stress test outcome (such as breaching regulatory capital ratios, illiquidity or insolvency) and then asking what events could lead to such an outcome for the bank. As part of the overall stress testing program, it is usual to include some extreme scenarios which would threaten the viability of the bank.

A sensitivity stress test measures the impact on a portfolio's value of a large change in a particular asset or in a smaller change that affects a number of correlated asset prices (assets whose prices tend to change together and exhibit covariant risk). One of the standard sensitivity stress tests used by risk managers measures the effect of a parallel shift in the yield curve that has an impact on the yields of short- and long-term bonds. Similarly, a sensitivity test might explore the impact of varying percentage declines in commodity prices or increases in interest rates on loans. A stress test scenario can be based on a significant market event in the past (a historical scenario) or on a plausible market event that has yet to happen (a hypothetical scenario).

How do surveyed bankers use stress analysis?

Based on responses to our small survey of community bankers, we can categorize how banks use stress testing in two ways: individual customer stress testing or stress testing a sector or industry. The results of stress testing can help banks manage their customers especially which fall into a higher risk categories. The survey shows that they obtain enough financial information for all of their customers annually to be able to stress test what they feel is appropriate.

Some banks first do individual (customer or loan) risk ratings and then, based on the resulting risk categorization, they do stress testing. Bankers indicate that individual risk ratings are often based on prior year actual profit (loss), current balance sheet information, and current loan-to-value ratio information. One banker indicates that this is done on an actual year-end basis and also on a projected (pro-forma) basis. This yields a new risk rating after the loan is made which can sway the rating given the size of the transaction. An example from one bank is a young farmer with good net worth position and limited debt could have a low risk level, but after purchasing land (and borrowing most of the purchase price) his score changes to a high risk level due to a lack of equity and a high loan-to-value ratio. After risk ratings are done, banks indicate that they perform individual stress tests on an annual basis at the time the credit is reviewed for the coming year's credit requests. The survey responses generally suggest that the criteria for the stress tests are established at least annually.

Some banks do other kinds of stress testing on a weekly basis and then use the results along with a watch list. The methods banks use to stress-test may combine a "what-if analysis" with an evaluation of past deviations. For example, one community bank performs "shock tests" each week, testing and then back testing, and risk assessment is done annually on individual clients. This community bank tracks and monitors changes in the whole loan portfolio. The surveyed banks respond that a watch list is extremely important to keep tabs on high risk credits throughout the year.

Survey banks also do stress testing at the sector or industry level. Some banks assess risks based on North American Industry Classification System (NAICS) code.[1] The NAICS code classification allows a bank to track delinquency and loss trends by industry so that stress testing can be implemented selectively on high-risk industries. One bank indicates that all nonconsumer loans are coded with NAICS codes to measure industry concentrations which allow the stressed industries to surface via the risk rating scores.

Bank respondents indicate that the subsector designation carries with it important information about income potential. For example, one bank knows that the grain industry has been performing well in the recent past, while the swine and dairy sectors have experienced significant financial stress. For this reason they assess many agricultural industries at least annually. One bank reveals that its agricultural industry portfolio is segmented by product (i.e., almonds, feeder livestock, ethanol, dairy, hogs, crop production, vineyards, etc.). Though the survey respondents do not specifically mention how they do stress testing or trend analysis at the sector or subsector level, they likely stress test subsectors where earnings are under downward

[1] The NAICS is the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. business economy. NAICS was developed under the auspices of the Office of Management and Budget (OMB), and adopted in 1997 to replace the Standard Industrial Classification System (SIC) code.

pressure or where high loan concentrations exist. Surveyed banks monitor this through the loan concentration report where they break the portfolio down into several subsectors.

To sum up, the surveyed banks provide general indications on the information and the factors they track as they stress their loan portfolios. These stress tests are performed at least annually. Banks do stress testing on their portfolios at the individual level based on credit scores, and at the industry level by focusing on the high risk segments of their portfolios. Based on the results of their stress analysis they may form a watch list for monitoring purposes, use the results to manage high risk loans, or use the results to determine if more capital is needed.

Some banks appear to use NAICS code designators to capture "macro factors" when performing stress tests, but there is no common approach in use. An example is found in the dairy industry portfolio at one of the responding banks where dairy loans are monitored due to the current low level of milk prices. Yet, the bank really wants to obtain information about how economic conditions will change in that sector (i.e., industry outlook or guidance). Some banks also mention that other economic factors are important drivers of their approach to risk assessment, such as the foreclosure rate, regional unemployment rate, etc.

How do surveyed bankers use trend (benchmark) analysis?

Banks use benchmark analysis to help them identify high risk customers. Surveyed banks indicate that segregating borrowers within an industry highlights the weakest borrowers. One bank mentions that benchmarking allows them to concentrate on the extent to which improvement is required or there is a need to develop an exit strategy if the level of risk appears to be excessive for individual borrowers or for subgroups of similar borrowers.

Surveyed banks use a variety of tools to perform trend/benchmark analyses and they use various databases to track information, analyze trends, and share information. Several of the surveyed banks use similar loan information systems to track information across loan segments. For example, one bank responds that the same factors are used in the commercial loans and agricultural loans, but they apply different weights to these factors.

One bank responds that it shows the results of benchmarking to its customers to let them know how they compare to others in their peer group. The bank responds that over time, individual borrowers can learn about what changes they made that caused their competitive position to change and areas in which to concentrate in order to improve their position. The bank creates this “dashboard report” and offers it to their customers. The report includes graphs that compare each customer’s financial trends to an average of the rest of their portfolio and also by location.

Some banks respond that they do benchmark analysis to let their staff know which clients require more attention. For example, one bank indicates that by benchmarking individuals against the portfolio on a quarterly basis, they can “earmark” borrowers that may cause a loss to the bank. After doing benchmarking, some of them banks create watch lists. One bank reveals that it has weekly loan committee meetings that address all watch, substandard, and doubtful credits throughout their entire bank.

Do community banks have special needs?

Based on the survey responses, there is a common core set of needs among banks. For example, they use national economic factors and industry trends as part of their approach to adjusting the general allowance for loan loss. They also want to be able to access more detailed information about national economic conditions sooner so that risks can be mitigated earlier. Also, banks reveal that it would be helpful to be able to easily do more analysis by enterprise, county, land type, etc.

For retail loans one bank uses its historical charge-offs and performs calculations to make additional allowances as needed. Some banks indicate that they want to know what factors to use when determining an adequate loan loss reserve amount. Surveyed banks also indicate that they want to know more about how to determine the likelihood of loan default and loss given default, and how those apply to stressed industries and different loan types. These factors are important when determining the adequacy of the bank’s capital position.

None of the banks report using a formal credit risk portfolio model. And they do not estimate the probability of default, loan recovery rates or loss given default, indicators of credit risk migration, or the correlation relationship between loans. Yet, generally bankers respond that they want to learn more about these concepts and how they can be applied in credit risk portfolio analysis.

Banks use different kinds of software to perform their risk assessments. Among those reported are Web Equity, ViewPoint, FisCal (commercial), FINPACK (agricultural), and Microsoft Access. While banks may combine the use of several tools most of them use Microsoft Excel. Some banks use Access and Excel jointly to manage their loan data base and perform stress and benchmark analyses. A primary challenge in this regard is having the tools to easily access loan information and put it in a form that allows for analysis. Web Equity accomplishes some of that task.

IV. Conclusions

We find that there are significant gaps between what community bankers indicate they are doing to assess credit portfolio risk and what the research literature provides. While several of the methods that are identified in the research literature are not used by smaller community banks, this specific gap is not amenable to a simple explanation. Banks perform stress analysis, trend analysis, and create watch lists of loans and clients. These banks typically do not perform a portfolio level risk analysis, as described in the research literature. So, what are some characteristics of the types of methods and tools that might help to fill that perceived gap?

The survey indicates that bankers already do stress testing based various scenarios and other factors. So, the facility to perform stress tests should be a feature of any risk assessment tool. These stress tests should be performed at the individual borrower (loan) level, at the sub-portfolio level, and at the aggregate bank portfolio level. In addition the research literature is relatively silent on which factors to use in stress testing, which measures of portfolio performance should be stressed, or what specific methods to use when performing stress tests. The typical approach to stress testing in the literature is to generate a value-at-risk (VaR) measure, yet most small banks do not estimate such a measure even though it is relatively easy to do. What other measures of risk exposure might be equally, or more, useful?

From the survey, we know that community bankers want to understand their risk exposure in the agricultural industry. Yet, conditions in agriculture can differ greatly due to a number of factors including the volatility of farm commodity and input prices. Also, there are potentially important sources of systematic (correlation or covariance) risk that are present at the subsector level and across borrowers. So, risk assessment tools and methods should incorporate elements of the correlation structure that reflect this degree of interdependence at the whole portfolio, at the subsector portfolio, and at the individual borrower (loan) levels of exposure.

Finally, the particular measures of portfolio performance that a bank evaluates should consider the trade-off between portfolio risk and expected profitability. The profit side is potentially captured by measures such as risk-adjusted return (or risk-adjusted return on economic capital) or expected value added. On the risk side, the measure could be a marginal risk indicator, or an indicator of the likelihood of default. When identifying these measures and developing the tools that produce them, it is also important to realize that community banks may lack sufficient data to implement some of the risk assessment tools that are found in the research literature.

In a second paper we will propose a methodology for portfolio analysis that will help to bridge the gap between what the research suggests be done and what bankers do. In that paper we use visual portfolio analysis to illustrate how community bankers can analyze their risk exposure and migration patterns and perform simple stress tests.

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