
Credit Risk Assessment

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Abstract

Lenders, regulatory agencies, and investors have increased their demand for credit risk exposure information to appropriately price risk and evaluate risk migration patterns that affect institution safety and soundness. This review provides a synthesis of the advances in credit risk assessment made through journal articles and other professional reports. Contributions in three primary areas are considered: (a) how the credit risk assessment problem has been defined and redefined over time in response to the changing information needs of lenders and regulators, (b) how methodological innovations have improved credit assessment procedures, and (c) how the efficiency of financial markets has changed due to the evolution of credit risk assessment. The paper concludes with a discussion of how transactional and relationship lending approaches are expected to evolve in the future and whether measures can be developed to more accurately assess factors such as management capacity and commitment to repay.

Key words: credit evaluation, credit risk assessment, credit scoring, loan default, loan repayment

Analysts, policy makers, and practitioners have recently focused greater attention on credit risk assessment and capital adequacy following adoption of the new Basel II Accord which provides incentives for lenders to measure probability of default (PD) and loss given default (LGD) in their loan portfolios. Early credit scoring and other risk assessment tools primarily assisted lenders with delineating borrower characteristics associated with default. More recently, lenders, regulatory agencies, and investors have increased their demand for credit risk exposure information to appropriately price risk and evaluate risk migration patterns that affect institution safety and soundness.

This review provides a synthesis of the advances in credit risk assessment made through journal articles and other professional reports. Contributions in three primary areas are considered: (a) how the credit risk assessment problem has been defined and redefined over time in response to the changing information needs of lenders and regulators, (b) how methodological innovations have improved credit assessment procedures, and (c) how the efficiency of financial markets has changed due to the evolution of credit risk assessment.

A novel feature of this paper is that it compares transactional versus relational approaches to credit risk assessment. A constant struggle with respect to development of credit assessment models has been to appropriately balance quantitative and objective financial data with subjective measures of borrower behavior. Traditional credit risk assessment literature has focused on developing credit risk assessment tools (such as credit-scoring models) which are utilized in assessing loan transactions or

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individual borrowers. While these approaches are also heavily utilized in relationship lending, the lender also evaluates a variety of factors such as management capacity and commitment to repay, which are frequently assessed by developing a relationship with the borrower. The paper discusses how the transactional and relationship lending approaches are expected to evolve in the future and whether measures can be developed to more accurately assess factors such as management capacity and commitment to repay.

Defining the Credit Risk Assessment Problem

The fundamental problem of the lender is how to accurately evaluate credit risk exposure at the transaction and portfolio levels because, as the level of credit risk increases, the realized rate of return on a loan portfolio is reduced and the required level of capital increases. This is a primary concern for lenders (and their shareholders), their regulators, and their borrowers.

The working hypothesis behind models developed to solve the credit risk assessment problem is that borrower creditworthiness can be determined by applying statistical models to measurable characteristics of borrowers at the individual transaction level. The results from these formal credit-scoring models (CSMs) can be used to predict the likelihood of repayment (default). There is no standard usage of the term "formal" in the literature (Ellinger et al., 1992). However, a formal credit evaluation procedure might refer to a pre-specified process used across all, or a class of, borrowers for the purpose of determining the risk of a farm borrower. The procedure incorporates specific measurable factors that predict the likelihood of repayment and that can be used to assign borrowers (or loans) to distinct risk groups to reflect their relative creditworthiness.

There appears to be relatively limited explicit recognition of the fact that there are costs to borrower misclassification in the credit risk assessment literature. LaDue (1989) reminds us that the cost of making a loan to a borrower who eventually defaults (i.e., a type I error occurs when a problem borrower is classified as an acceptable borrower) is different from the cost of not making a loan to a borrower who fully repays (i.e., a type II error occurs when an acceptable borrower is classified as a problem borrower). But credit-scoring models typically do not incorporate these misclassification costs, and the models have not differentiated between the various degrees of default that exist in a loan portfolio. These shortcomings appear to be related, and may be due to the lack of adequate data for estimating the costs.

The impetus for the development of agricultural CSMs during the late 1980s and early 1990s has been attributed to the large number of farm failures and loan defaults among farm borrowers in the United States in the early 1980s (Turvey, 1991). In addition to controlling and monitoring credit risk exposure, it has been suggested that 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 and management objectives (Ellinger et al., 1992).

The use of CSMs generates the potential for endogeneity in the credit risk assessment problem. This may occur in two ways. As the model is applied to the population of borrowers to differentiate good from bad borrowers, a disproportionate share of good borrowers "survive" (i.e., they make good investments and increase their profitability over time, improving their qualifications for future loans), while the opposite is true of the proportion of bad borrowers. Thus, repeated sampling over time from the population of borrowers makes it progressively more difficult for the model to differentiate good borrowers from bad borrowers. Moreover, if there are

errors in the level of prediction accuracy of a model, those errors may be carried forward in successive applications of the model. Consequently, lenders need to periodically reestimate and update their CSMs.

How do credit-scoring models compare to portfolio models when looking at the credit risk assessment problem? Portfolio models of credit risk exposure do not focus directly on producing credit scores; rather, they take a more macro view of the problem. The portfolio view examines the level of default risk exposure in sub-portfolio segments and the correlation between those sub-portfolio segments in terms of their likelihood of default. Although different portfolio models exist, they generally focus on determining and monitoring capital requirements (economic capital) in order to cover expected credit risk exposures.

Early Credit Risk Assessment (pre-1990)

Determining the risk of both existing and potential agricultural loans has been described as the most important job responsibility of an agricultural loan officer. In addition to default risk, loan officers are also interested in minimizing time spent monitoring adverse loans and incurring the costs of delayed or partial repayment (Gustafson, Saxowsky, and Braaten, 1987). Both can be quite costly to a financial institution. Moreover, the credit status of a farm borrower could affect loan pricing as well as other nonprice factors (fees and collateral requirements). Regulators and investors also have keen interest in lenders' evaluations of borrower risks.

Prior to 1970, lenders relied primarily on subjective assessments to appraise the credit risk of farm borrowers. Krause and Williams (1971) were among the first to link subjective characteristics of a borrower's personality with loan performance. How well the lender knew the farmer and the size of the loan were

two of the most important factors affecting interest rates paid by farmers according to Dahl (1962). However, as noted by Dahl, subjective assessments of borrower risk were quite informal and often led to discrimination. Today such lending practices would leave loan officers vulnerable to claims of lender liability. In their review of agricultural finance literature, Brake and Melichar (1977) reported that "few studies have examined the efficiency of lender operations or lending decisions. Lenders themselves could well undertake or sponsor more such work."

With the advent of computers, agricultural finance researchers actively developed more objective and quantitative decision criteria. One of the most popular efforts utilized discriminant analysis to distinguish between borrowers with good and poor credit risk based on their financial position and other loan application information provided. Brinegar and Fettig (1968) found capitalized expected future net returns to be highly correlated with loan performance. Bauer and Jordan (1971), Johnson and Hagen (1973), Evans (1971), and Reinsel and Brake (1966) estimated discriminant functions and attempted to link information on loan applications with loan success probabilities. The results of their efforts were mixed. The latter two studies in particular were not very robust, as results varied by length of patronage and lending institution, respectively.

Similar ambiguity in credit evaluation occurred in other financial markets prompting the Board of Governors of the Federal Reserve System to develop criteria for determining when a credit scoring system is statistically sound and empirically derived (Bieber, 1985). In essence, any model developed must be robustly estimated with both creditworthy and non-creditworthy borrowers, be validated, and updated over time.

Dunn and Frey (1976), Hardy and Weed (1980), and Hardy and Adrian (1985) improved the application of discriminant

analysis and variants of the technique with the addition of more explanatory variables and differing geographic regions. Results were still limited to Farm Credit System data, however. Leatham (1987) described the usefulness of these approaches for different lending functions. He also constructed a chart comparing the explanatory variables and approaches of the discriminant studies discussed above.

While these more quantitative approaches were being refined, several other researchers developed lender decision aids based on more subjective, experiential information—striving to find the balance between subjective and objective measures. Allcott (1985), Kohl and Forbes (1982), and Kohl (1987) proposed methods that included more comprehensive financial measures (liquidity, solvency, profitability, efficiency, repayment capacity, and management ability) and incorporated data from commercial banks. However, performance and validation measures were unavailable for evaluation.

Significant advances occurred in the 1980s, when even greater computer power and new statistical methods provided more opportunity for quantitative approaches. Fisher and Moore (1987) noted past discriminant approaches were limited because they assumed multivariate normality of explanatory variables, an unlikely assumption with financial ratio data. They proposed a logistic function which was not only more accurate, but relied on fewer explanatory variables. In favoring this objective approach, they conclude that subjective assessments “have undesirable implications for customer relations and possible adverse legal consequences.”

Miller and LaDue (1989) and Turvey and Brown (1990) extended and refined the logistic method. Miller and LaDue dealt with several methodological issues. They specified the dependent variable more accurately with actual borrower repayment data. Instead of relying on subjective

lender or examiner assessments; delineated credit screening and loan review applications; grounded selection of independent variables based on ratio theory; considered costs of misclassification; and utilized a hold-out sample to test validity. Turvey and Brown incorporated covariance to account for regional and farm type differences.

In the later 1980s, credit-scoring models were integrated with other financial institution and farm decision models. The resulting insights clearly illustrated the jointness of credit and other firm managerial decisions. Lufburrow, Barry, and Dixon (1984) were among the first to link credit assessment with loan pricing using a probit model. Results enabled lenders to advise borrowers about factors that comprise credit scores and changes that could be undertaken to improve their classification.

Stover, Teas, and Gardner (1985) examined the interacting effects of farm loan decisions with credit considerations in the decision process of lenders. Mortensen, Watt, and Leistritz (1988) extended these results by linking credit scores, loan pricing, and lender revenue functions. Barry and Ellinger (1989) developed a multi-period model that endogenized credit, investment, and loan pricing decisions. Barry, Baker, and Sanint (1981) and Sanint and Barry (1983) considered credit risks jointly with other financial and business risks using mean-variance portfolio theory.

The need to develop credit assessment models that were more useful to lenders was paramount. The basic steps of developing a credit-scoring model were conveniently summarized in lay terms to facilitate expanded adoption by lenders (Barry et al., 2000):

- Identify key variables that best distinguish among borrowers' creditworthiness,
- Choose appropriate measures for these variables.

- Weight the variables according to their relative importance to the lender.
- Score each loan as a weighted average of the respective variables, and
- Assign the credit scores to the appropriate class.

Development of broad and robust models of credit assessment was still stymied by lack of consistent financial information across lending institutions, regions of the country, and farm types. Information-intensive quantitative models required more standardized data for estimation and validation. LaDue (1990), in cooperation with agricultural bankers, was instrumental in organizing such an effort leading to the creation of the Farm Financial Standards Task Force that provided this information. The resulting 16 financial ratios and methods of calculation are now widely adopted in the industry.

In addition to model development, the profession has actively critiqued itself by periodically reviewing progress and identifying voids requiring further development. The first type of review has been a self-critique conducted by peers. Studies by Leatham (1987) (mentioned earlier) and Gustafson (1987) were commissioned by Regional Research Committee NC-161. Both papers note that few financial institutions adopted early evaluation models, although their usefulness had been substantiated. Gustafson (1987) advocated use of portfolio analysis to examine contributions of individual borrowers to total portfolio risk.

A series of American Agricultural Economics Association invited papers in 1989 further document the role of credit evaluation in agricultural finance. Chhikara (1989) found that existing credit-scoring models have been limited by an exclusive focus on default rates. Like Gustafson (1987), he encourages development of portfolio and multi-period models that consider inclusion of expert models which incorporate more subjective variables.

Gustafson (1989a) suggests credit assessment techniques can be utilized to judge the sector's financial health. He also urges development of dynamic credit evaluation models, greater inclusion of behavioral indicators, and measures to evaluate the health of agribusinesses and international firms as concentration within the sector progresses. Gustafson (1989b) estimates the value of credit-scoring models in general, in addition to the value of a dynamic credit assessment. In reviewing the above papers, LaDue (1989) encouraged more focus on costs of misclassification and definition of credit. He also stressed the need for more accurate financial data, including forward-looking measures. In his review, Obrecht (1989) reminds us to remember the events of the 1980s farm financial crisis and incorporate them in our methods.

Finally, in LaDue's (1989) summary of NC-161 Regional Research Committee accomplishments, he reported that the credit scoring subcommittee "was the most active ... focusing on credit scoring and loan evaluation." LaDue noted out-of-sample properties for many of the models were acceptable, but variables contained in these models were quite diverse. Turvey (1991) compared and contrasted the performance of four alternative credit evaluation models—discriminant analysis, Probit, Logit, and linear probability. Despite differences in underlying assumptions, classification accuracies were similar for all approaches.

The second type of review was to actually gauge acceptance of the profession's research by the lending industry—the eventual purpose for which all these models were developed. Miller et al. (1993) surveyed 1,027 Midwest commercial banks and found growing use of risk-adjusted interest rates based on banks' ability to delineate credit risk among borrowers. Nonprice factors (fees and collateral requirements) also varied by risk class. Ellinger et al. (1992) report the findings of NC-161's regional research survey conducted to determine lenders' use of credit evaluation procedures, the extent to

which they are utilized, and whether these procedures are used for loan approval and pricing. Findings revealed that 62% of respondents used a formal credit evaluation method, with the proportion increasing with bank size. Lack of quality borrower information was a deterrent to use. Finally, Gustafson, Beyer, and Saxowsky (1991) conducted in-depth interviews with 10 loan officers to determine their information sources, credit evaluation procedures, and lending heuristics. Lenders surveyed employed conservative credit evaluation techniques and based credit decisions on borrowers' collateral positions, level of compensating balances, and character.

Until this point, it was assumed borrowers and lenders had equal information (or lack thereof). Underlying the credit risk assessment problem is an asymmetric information problem that is characteristic of all lending environments. Asymmetric information produces two related problems for a lender—*adverse selection* and *moral hazard*.

Adverse selection occurs when the lender is unable to distinguish between high- and low-risk borrowers. For example, a lender cannot simply charge an interest rate that equates to the risk of an average borrower, because only borrowers with risk at or above the average will agree to the loan terms (Stiglitz and Weiss, 1981). At higher interest rates, only high-risk borrowers can afford the rate and expected profit drops because credit risk drastically increases due to the loss of low-risk borrowers.

Moral hazard is the ability of a borrower to use loan funds to engage in activities that are riskier than the lender anticipated. Only the borrowers can know their true intentions for the loaned funds and their future ability and willingness to repay the loan.

A new line of research developed in the late 1980s assumed borrowers had more knowledge about their eventual credit risk than their lenders because they are more

familiar with their business, financial position, and repayment intentions. Borrowers then have incentive to find lenders who allow them to undertake riskier actions, which increase likelihood of default (Robison, Barry, and Burghardt, 1987; Foster and Rausser, 1991). Gustafson (1987) foresaw this problem and urged researchers to place more emphasis on the mindset of borrowers to "identify a subject's state of knowledge and infer a model of cognitive process that is useful for prediction of observed behavior."

Lenders have responded to these problems of asymmetric information and adverse selection by focusing more closely on relationship information including borrower motivation, commitment, and intentions. These subjective characteristics are not directly observable in loan documents presented by borrowers. Lenders' attempts to obtain more personalized relationship information from existing and prospective borrowers is the topic of the next section.

Recent Credit Assessment Models (post-1990)

Multivariate, accounting-based credit-scoring models have been criticized due to their lack of a theory and their failure "to pick up more subtle and fast-moving changes in borrower conditions" (Caouette, Altman, and Narayanan, 1998, p. 134). Nonetheless, we observe that the agricultural finance literature on CSMs has developed through a series of experiments with alternative statistical models and data sets with varying degrees of success. The literature provides a useful description of several alternative statistical approaches which might be used for credit scoring (Chhikara, 1989). Yet, the research literature also reveals a paradox. There appears to be a reasonable level of consistency between these models when selected alternative model estimation techniques and a common borrower data set are used (Turvey, 1991; Ziari, Leatham, and Turvey, 1995). However, there is an apparent lack of consistency between the

actual models developed and used by different banks when applied to a common borrower data set (Ellinger, Splett, and Barry, 1991, 1992; Ellinger et al., 1992).

For example, Turvey (1991) reviews some commonly used parametric techniques for CSM estimation—linear probability models (LPMs), discriminant analysis (DA), and regression (Probit and Logit). Although Turvey's results are not conclusive, these alternative techniques are found to provide relatively similar predictive power, even though they employ somewhat different underlying assumptions. The LPM and DA techniques pose specific problems for model estimation (e.g., correction for heteroskedasticity in the case of LPM and the assumption of normally distributed random variables in the case of DA). The Probit and Logit model specifications have been more appealing, with the Logit estimation being less restrictive in terms of the underlying distributional assumption.

Ellinger, Splett, and Barry (1992) applied 87 different CSMs used by banks to a common set of 324 loan cases in order to evaluate the consistency between models—both consistency of credit scores across loan cases of different types and consistency of models in the loan rankings that are produced. They found there is no uniform model for lenders to use, but overall model consistency was better when predicting low-performance cases than when predicting high-performance cases. Loan rankings were shown to be positively correlated, but there were large variations. The observed diversity among the tested models was attributed to: (a) use of many different measures to estimate the variables, (b) differences in the incorporation of subjective measures (e.g., management), and (c) use of data from different points in time during the loan period to develop the models.

One general explanation for the apparent contradiction is that the models used by banks may differ due to: (a) different purposes of credit scoring (e.g., loan approval versus loan pricing), (b) differing risk attitudes of lenders, or (c) different

types of borrowers and quality of information available to the lender (Ellinger, Splett, and Barry, 1992). A second general explanation might be that many such models are not adequately validated, given the short history of their development and use, and the potentially wide variation in data employed in their development. Thus, it is not surprising that a significant part of the recent agricultural finance literature has focused on the potential for improving the consistency (or robustness) of the models. We consider this literature in two ways—variations in model specification and variations in efforts to validate the models.

Model Specification

Miller and LaDue (1989) suggest that no specific factor has consistently been used to evaluate credit risk in the credit scoring framework, and the credit risk classifications from lenders and loan files tend to vary across research studies. Indeed, the literature reveals there are concerns over which factors to include as predictors of loan quality, how uniformly the factors are measured, how the models apply to different farm and loan types, and how well the models perform over time.

Lufburrow, Barry, and Dixon (1984) include measures of borrower liquidity, leverage, collateral, repayment ability, and repayment history. Miller and LaDue (1989) include profitability, leverage, and efficiency measures. Turvey and Brown (1990) incorporate liquidity, profitability, leverage, efficiency, repayment ability, farm type, and region as predictors of loan default.

A later survey of agricultural bankers indicates a similar wide range of financial and nonfinancial factors and factor weights are used in practice. In these models, high importance is given to borrower solvency, liquidity, repayment capacity, and collateral position (Ellinger et al., 1992). Splett et al. (1994) found different model specifications apply to term loans and operating loans.

Gallagher (2001) added nonfinancial characteristics of loans (combined manager and lender experience, and the use of a financial adviser) to predict the success of agribusiness loans. As reported by Zech and Pederson (2003), factors such as family living expenses and farm financial efficiency are excellent predictors of overall financial performance, even though they are frequently excluded from CSMs. Thus, model specification continues to be an issue for researchers and practitioners.

Model Data and Validation

In order to further improve the consistency and robustness of CSMs, several researchers have considered the importance of how factors are measured and how the resulting models are validated. Novak and LaDue (1994) raise two questions for CSMs generally: Does extending the time horizon of a credit score affect the ability to classify borrowers? And if so, what time horizon produces a reliable model result? They showed that multiple-year averages of variables can improve the stability of model parameters and the predictive accuracy of models when compared to models derived from individual year data. Novak and LaDue attribute the improvement in model performance to "smoothing effects" and the extension of the period of creditworthiness. This general finding has been confirmed in other studies (e.g., Turvey and Brown, 1990; Zech and Pederson, 2003).

A further effort to foster model consistency and robustness is found in the practice of model validation using out-of-sample testing. Model validation may be accomplished by testing the estimated model using hold-out sample data from the same period, or by testing the estimated model's ability to predict hold-out sample data outside the sample period. For example, Turvey and Brown (1990) use a series of tests to validate an estimated national model for Canadian farms. They use an estimated model to predict the incidence of loans being current in the subsequent two years and then compare

the model results to actual results. Zech and Pederson (2003) estimate models for repayment ability and financial performance using three-year averages, and validate the models by predicting the creditworthiness variables for the next two years. In each of these studies the validation step is shown to differentiate the most significant predictors from those having relatively limited predictive ability.

Through this period of model development and testing, efforts have been made to identify a set of uniform financial standards for use in farm financial analysis. The Farm Financial Standards Task Force (FFSTF) has produced a set of common financial factors (profitability, solvency, etc.) and 16 financial variables agricultural lenders can adopt for use in credit-scoring models. The expectation is that widespread adoption of these measures will lead to greater uniformity of the variables which are derived from farm data, and potentially greater consistency in the CSMs developed by bankers.

Aggregate (Sectoral) Models

While CSMs have typically focused on analyzing data at the individual transaction level, Oltmans (1994) approached the loan assessment problem from an aggregate perspective. Ordinary least squares (OLS) regression is used to identify early warning models using farm sector data on collateral values, changes in farmland values, debt/asset ratios, government payments, and off-farm incomes to predict changes in loan quality in Farm Credit System institutions.

Additional tests of the estimated aggregate models indicate they outperform simple time-series models that use lagged loan quality indicators to predict future loan quality changes. Thus, changes in the fundamental financial indicators appear to be better predictors than trends in the time series. In addition, the aggregate approach to loan quality assessment may be combined with individual borrower analysis to increase the range of tools

available for portfolio analysis and risk management.

Nonparametric Approaches

While statistical credit-scoring models have expanded in use, they require the user to accept restrictive distributional assumptions which may undermine the reliability of the model results. For this reason, researchers have tried nonparametric approaches (such as recursive partitioning algorithms and mathematical programming techniques), and compared their results to those obtained with parametric (statistical) approaches. The results suggest that a recursive partitioning algorithm outperforms parametric models, such as discriminant analysis or Probit and Logit regression, in terms of classification accuracy (Chhikara, 1989). Further testing of this finding is needed.

Ziari, Leatham, and Turvey (1995) also found mathematical programming techniques perform as well as statistical models (and mixed integer programming models actually outperform the statistical models). The additional advantages of mathematical programming approaches are that they can accommodate various objective or criterion functions and sensitivity analysis can be readily performed. Both nonparametric approaches have the additional feature that misclassification costs can be incorporated into the model.

Best Practice in Credit Assessment

One of the objectives of applied research on credit risk assessment models is to identify good model characteristics, or what might be termed as "best practice." What does the agricultural finance literature indicate about these general characteristics?

Several studies suggest that model specification and validation are quite important to improving model consistency and accuracy. Greater attention to these

factors will provide greater confidence in the model and less room for classification errors. Models need to be adequately validated by testing the predictive ability of the model when applied to out-of-sample data.

Various studies have also shown that using multiple-year averages of predictor variables in the models improves model parameter stability and model accuracy. Quantitative and qualitative variables need to be included where possible to improve model predictive ability. Descriptive variables for differences in farm type and geographic region may be desirable when the data allow them to be included in the model. Nonfinancial factors such as the experience of the loan officer should also be considered in the development and testing of CSMs. When the available data are characterized by small sample size and/or the data are heavily contaminated, mathematical programming may be a better tool for model estimation.

Credit Risk Migration

Recent attempts have been made to apply migration analysis to the credit risk of agricultural lending. A credit risk migration rate measures the probability that an asset will be in a certain credit risk class in a future time period given a current credit risk classification. Early credit risk migration research was performed by analysts looking for ways to predict future price movements of debt instruments such as bonds. For example, Altman and Kao (1992) analyzed S&P bond data from 1970–88. This and other research have evaluated the time homogeneity of ratings and the effect of the business cycle on those ratings. These two topics continue to be key issues in migration analysis today.

Due to the lack of sufficient agricultural loan risk-rating data, several previous applications of migration analysis to agricultural lending have used farm-level data. For example, Phillips and Katchova (2004) test for path dependence using the annual migration rates of credit scores

which are derived from the Illinois data in Barry, Escalante, and Ellinger (2002). The authors use annual credit score migrations so that they can condition on the business cycle. Two-sided t-tests and the singular value metric are used to show the presence of a trend reversal pattern in the migration matrix. Upgrades (downgrades) tend to be followed by downgrades (upgrades). They condition migration rates on three stages of the U.S. business cycle (as defined by the National Bureau of Economic Research). The singular value metric and cell-by-cell analyses show that upgrades are more likely to occur in an economic expansion phase. The opposite is true for an economic recession.

Similarly, Escalante et al. (2004) use credit scores based upon farm-level data from Illinois to represent credit risk. An ordered probit regression is used to determine path dependence while accounting for demographic, financial, and macroeconomic variables. The macroeconomic variables which are influential on loan risk migration include farmland value, aggregate money supply, the S&P 500 Index, and long-term agricultural interest rates.

Gloy, Gunderson, and LaDue (2005) perform a credit risk migration study on loan-level data provided by agricultural banks. This approach has the advantage of using credit risk ratings that are determined using the resources and methods agricultural lenders have available to them. A logistic regression model is used to detect factors influencing credit downgrades. Based on their findings, the probability of a downgrade differs across lending institutions. In addition, young borrowers and farm businesses in the declining stage of their life cycle are more likely to experience a downgrade. Their results show that livestock and horticulture operations are less likely to experience a downgrade than annual crop, permanent plantings, or other types of farms. At this early stage of research on risk migration, none of these previous analyses have simultaneously accounted for the influence of previous

migrations, the economic cycle, and other important determinants.

The Future “R’s”: Regulations, Relationships, Robustness

The future of credit risk assessment can best be understood by viewing credit risk from the financial institution managerial perspective and the regulatory perspective. The primary focus of a managerial perspective is on accurate underwriting and pricing of credit risk. Accurate credit risk assessment helps management decide whether the credit risk posed by a borrower is acceptable given the institution’s desired risk-bearing capacity.

From a managerial perspective, the accuracy of credit risk assessment serves two key purposes. First, it removes from consideration borrowers who present excessive credit risk. Second, for those borrowers who pass the first screen, it is used to determine how much credit should be extended and what price should be attached to an extension of credit. In this way, credit risk assessment serves the purpose of helping institutions align expectations of the risk and return with constraints on portfolio performance.

Both of these decisions play a critical role in determining the level and variability of the financial institution’s earnings. Of course, the variability in earnings plays a key role in determining changes in the balance sheet of the financial institution. Large negative earnings reduce the capital of the institution and threaten its safety and soundness. This is where the regulatory perspective on credit risk assessment becomes important.

The primary focus of the regulatory perspective is to ensure that the institution’s capital is not compromised to an extent whereby the soundness of the institution comes into question. The primary regulatory concern is whether adequate capital has been allocated to account for credit risk. Less concern is

focused on whether credit risk has been accurately priced. Instead, regulators are concerned whether credits carry too much risk, regardless of price.

The Basel II agreement is an important step in the regulatory approach to determining capital adequacy standards. The agreement is related to credit risk assessment because the advanced internal ratings approach outlined in the Basel II makes explicit use of internally generated estimates of the probability of default, loss given default, and exposure at default when calculating a financial institution's capital ratios.

While only the largest, multi-national financial institutions will be required to adopt the advanced internal ratings approach to determine capital adequacy, Barry (2001) points out that the agreement reflects the latest thinking in capital management. Barry offers a discussion of three pillars of the Basel II agreement and discusses how they might apply to agricultural lenders. The agreement provides additional information regarding modern capital management practices which may be used to improve and enhance credit risk assessment in banks and the Farm Credit System. However, the data and methodological requirements for the more advanced approaches to determining capital adequacy are substantial, and many agricultural lenders will not be able to comply with them.

As institutions begin to adopt ideas contained in the Basel II agreement, many will attempt to place a value on the credit risk contained in their portfolios. The literature on valuing the amount of credit risk held by an institution continues to evolve. An example of this research is an analysis by Sherrick, Barry, and Ellinger (2000), who estimated the cost of insuring pools of agricultural mortgages. Likewise, Katchova and Barry (2005) applied the CreditMetrics and Moody's KMV model to farm-level financial data to estimate capital requirements under Basel II principles.

Implications of the Managerial Perspective: Loan Costs and Pricing

The earlier review of research indicates a strong focus on the first component of the managerial perspective and the related regulatory perspective. Namely, what is a borrower's probability of default, or what is the likelihood that the borrower will fail to repay her obligations to the financial institution? While this is a critical question for the managerial perspective, several managerial areas are in need of additional research. The most obvious is the clear need to accurately tie credit risk assessment to loan pricing. In order to make this linkage explicit, it is critical that researchers work to identify the costs associated with default and the additional costs associated with monitoring borrowers with greater credit risk. In short, unless one understands the costs which accompany increased likelihood of default, one cannot fully understand credit risk.

The likelihood of movement to default or to another credit risk category is only one component of the puzzle. Pricing must accurately reflect the associated costs of servicing marginal credits, including those that have not defaulted but require considerable oversight and monitoring.

Arguably the most important unresolved research issue relates to developing a better understanding of the distribution of loss given default in loan portfolios. Featherstone and Boessen (1994) examined the loan losses suffered on agricultural mortgages and estimated the average magnitude of losses at 29 basis points. While aggregate and financial institution-level data are available on loan charge-offs, there have been few attempts in agriculture to link these charge-offs to prior risk ratings or borrower characteristics.

Furthermore, there have been few attempts to estimate the additional operating costs associated with loan losses. These costs can be numerous. First, the institution must commit personnel time and

resources to recovering the loans. Second, the institution does not accrue interest on many of these loans. Third, there are often significant recoveries associated with agricultural charge-offs. All of these issues deserve further attention in the literature. Information regarding all of these data is critical to fulfilling the second key aspect of the managerial perspective. Without these data it is impossible to accurately estimate the interest rate that must accompany a higher risk borrower.

Further work is needed to examine the methods used by lenders to collect loans in default and to assess whether some collection processes are more effective than others. In addition, there has been little work directed at understanding what is happening with the borrower's business that impacts the likelihood of default, e.g., are there factors which often result in defaults? Instead, the previous research has focused on financial variables that illustrate the outcome (reduced credit quality) but shed less light on the factors that have resulted in the borrower's poor financial condition.

While loan losses are a critical component of the actual cost of increased credit risk, making higher risk loans also requires additional loan monitoring. These higher monitoring costs also influence the price of credit, making it an important factor in the likelihood that a borrower's credit risk increases even if the borrower does not actually default on obligations. Recent work on estimating the costs of delivering credit to different types of borrowers indicates it is much more costly to lend to very high-risk borrowers, while servicing and monitoring costs of low- and medium-risk borrowers are similar (Gloy, Gunderson, and LaDue, 2005).

Implications of the Regulatory Perspective: Credit Availability in Agriculture

The regulatory perspective has driven a substantial amount of the research on credit risk assessment. Financial institutions and their regulators appear to

be taking notice of the Basel II agreement. The Farm Credit System has recently undertaken efforts to standardize risk rating approaches and develop probability-of-default estimates (Anderson, 2004). As part of this process, an attempt is made to map default rates on different classes of agricultural loans to default rates on corporate bonds rated by Moody's and Standard & Poor's. Similar work has been undertaken by Featherstone, Roessler, and Barry (2004) who estimate the default rates on loans in the seventh Farm Credit District. Their findings suggest the default rate on an average quality loan in the district appears to correspond to the default rate on bonds in Standard & Poor's BB-rating category.

These recent attempts to relate agricultural credit risk ratings to corporate risk ratings come as regulators and investors express a desire for agricultural credit risk ratings to be reported in a manner that makes them comparable to the ratings developed by the ratings agencies such as Moody's and Standard & Poor's. As these efforts continue, work is needed to assist in determining how the ratings systems should be standardized and what data will be required to develop the ratings.

Designing Credit Risk Models for Relationship Lending and the Changing Structure of Agriculture

As agricultural lending continues to evolve, there are likely to be changes in the way credit risk is assessed and managed. Traditional agricultural credit risk assessment is based on a relationship whereby the lender gathers a considerable amount of financial data on the borrower and the borrower's business. The lender uses this relationship to obtain information and reduce problems of asymmetric information (discussed earlier). The loan officer spends considerable time gathering information about the farmer's business, assessing management capacity, and assessing the borrower's commitment to repay. This type of lending is costly because it involves

a substantial commitment of institution personnel.

Modern credit-scoring models (e.g., transactional lending) now allow lenders to make credit decisions without establishing a deep relationship between the borrower and lender. Instead, lenders place greater reliance on factors such as a credit bureau report and the output of the firm's own credit score when determining whether to grant credit, and less time is spent on traditional underwriting activities and relationship building.

The decision to apply the transactional model involves assessing the tradeoff between the cost of gathering additional information through a relationship and the benefit of reducing information asymmetry. It appears many lenders have decided that the risks associated with making errors on smaller loans are more than offset by the increased costs associated with the loan officer making this assessment, and that these measures may be at least as accurate as the loan officer's assessment. One important remaining question is to determine how the information gathered in the two approaches differs. And, if the additional information is obtained in the relationship model, can this information be standardized and incorporated quickly into credit-scoring models?

Implications for Different Types of Borrowers

The shift to increased reliance on credit scoring has many potential implications for the availability of credit to different types of borrowers. For many types of small farm borrowers, this means their creditworthiness will be assessed almost entirely by repayment history with the lender, their credit bureau score, and their current financial condition. To the extent these factors do not indicate all of the aspects of credit quality, some creditworthy borrowers will likely find it difficult to obtain credit. In other words, it will be too costly for the financial institution to overcome the adverse

selection problem. These types of borrowers will often be forced to rely upon credit cards as a source of agricultural operating credit, and their real estate loans will be treated much like residential real estate loans. Smaller borrowers with sound credit histories, however, will likely have little trouble obtaining credit. Using the Economic Research Service's farm typology (USDA/ERS, 2000), the farms most likely to be impacted by this trend are small family farms (limited resource, residential/retirement, lower and higher sales farming occupation). Of these, the most affected will likely be the lower and higher sales farming occupation farmers who may utilize operating lines of credit.

As farms continue to grow larger and more complicated, it will be critical for researchers and lenders to carefully consider the adverse selection and moral hazard problems associated with credit risk assessment. When lending to larger farms, it is essential the loan officer has the expertise to unwind the complicated financial arrangements characteristic of larger farmers. Many large farmers will make use of complicated hedging and risk management activities that, when used improperly, can actually increase risk. In addition, lenders will need to make sure they have control mechanisms in place which can monitor borrower activities. This will become increasingly difficult as the geographic size and location of these borrowers increase. Finally, accurate evaluation of management capacity on larger farms will be critical to making wise credit risk choices. Additional research is needed to help identify key indicators of borrower managerial capacity.

Conclusion

Development and refinement of credit risk assessment models has been an ongoing priority of agricultural economists. Over the past four decades, enhanced computational power and new analytical methods have enabled both greater estimation precision and breadth.

Researchers have rigorously tested the empirical performance and usefulness of estimated models on a routine basis. Moreover, as regulators created new opportunities for credit risk assessment, researchers responded and reformulated their models in an effort to meet this critical need.

Although considerable effort has been devoted to the problem thus far, many questions remain unanswered. The changing structure of agriculture will likely result in unique and individually estimated credit risk assessment models for each segment. Future credit risk assessment models will also likely vary depending on whether the resulting information is being used for loan assessment, regulatory, or individual producer decision making. The constant tension between transactional and relationship methods of estimation still exists and will no doubt continue. As in the past, new analytical methods and greater collaboration with other disciplines can be expected to result in relationships and models that provide even greater insight into the delicate interrelated decisions of borrowers, lenders, and regulators.

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